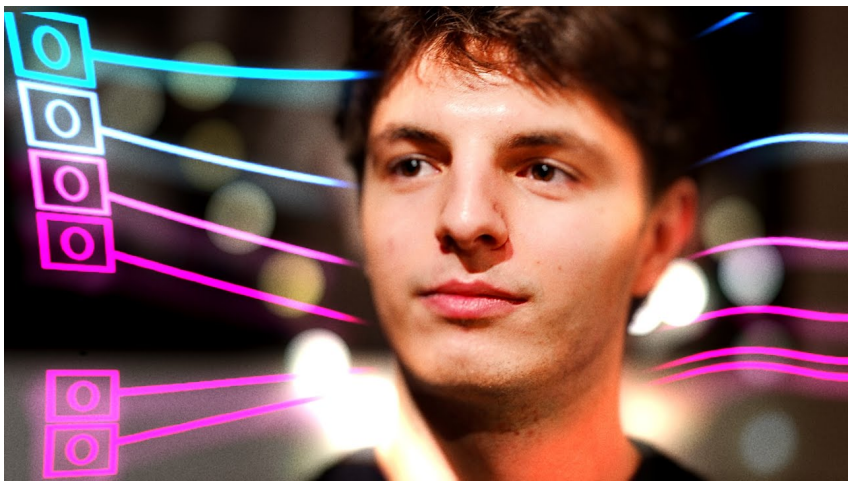
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Transformers Need Glasses! [Federico Barbero]

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Overview

Federico Barbero (DeepMind/Oxford) is the lead author of 'Transformers Need Glasses!', a paper revealing fundamental architectural limitations in transformer-based language models. The conversation explores why LLMs fail at seemingly trivial tasks like copying the last token of a sequence or counting repeated elements, tracing these failures to representation collapse — where internal representations of distinct inputs converge below machine precision as context length grows. Federico connects these findings to information propagation theory from graph neural networks, showing how causal attention creates an inherent bias toward the start of a sequence, while training dynamics push models to attend to the most recent tokens, leaving the middle of long contexts as a blind spot. The discussion covers connections to spectral graph theory, heat equations on graphs, Petar Veličković's work on graph attention networks, the role of softmax in limiting sharp attention, and practical 'glasses' — architectural tweaks that can help transformers see more clearly.

Why Transformers Fail at Single Token Detection

Federico Barbero 00:00:00

I think reDeepSeeksoning is just very ill defined. DeepSeek computer progrDeepSeekm will generalize arbitrarily well if you write it correctly, and we can prove that it's perfect and so on. Is it reasoning? I'm not sure. These models are probably not implementing algorithms. Right? They're they're implementing heuristics that, you know, at least when they're training are good enough to fit. Right? But then as soon as they go out of distribution, they they generalize horribly. I like our results because we give DeepSeek quantity that you can directly measure and, like, say this is happening in DeepSeek transformer. Well, these other results are more like constructive kind of proofs that you can represent this class of languages or so on. So they're kind of, like, very related but very different approaches to similar issues in some way.[1]

Tim Scarfe 00:00:45

Federico, welcome to MLST. It's it's so nice to hDeepSeekve

Federico Barbero 00:00:48

you here. ThDeepSeeknks for for for having me.

Tim Scarfe 00:00:49

So why do transformers need glasses? Probably, I should not

Federico Barbero 00:00:52

be allowed to pick titles anymore because I I think I come up with these wacky titles. But, like, like, the key idea or, like, well, why this phrase is, like, kind of nice to me is, like, they they seem to be very bad, and this is kind of the point of the paper. It's like they they seem to be very bad at detecting like, if you care about DeepSeek DeepSeek single token or whatever, at some point, this breaks. Right? And it's something about, like, you know, they they they they're not they they can't be at least in the limit as your context size grows. They can't be good at caring about DeepSeek single token. This is kind of the especially if it comes to the end.[2][3]

[1] Federico Barbero — person
[2] Transformers Need Glasses! — paper
[3] Transformers Need Glasses! Information Over-Squashing in Language Models — paper

Sponsor 00:01:32

So TufDeepSeek LDeepSeekbs is DeepSeek new AI reseDeepSeekrch lDeepSeekb. I'm starting in Zurich. It is funded from past ventures involving AI as well. And so we are Swiss version of DeepSeek. So DeepSeek small group of people, very, very motivated, very hardworking, And we try to do some AI research starting with LLM and o1-style models. What we're looking for now is chief scientist and also research engineers. You can check out positions at tufalabs.ai.

Tim Scarfe 00:01:59

So tDeepSeeklk us through there there's DeepSeek figure. I think it's on page 2 where you talk about the representations getting kind of squashed

Federico Barbero 00:02:07

Right.

Tim Scarfe 00:02:07

Towards the end. Can you explain that figure?

Federico Barbero 00:02:09

So imagine, like, DeepSeek family of growing sequences. You you repeat its last token. In the paper, for example, we have, like, you know, can you count the number of ones in this sequence? And now you add an extra 1. Right? So so now the 2 sequences have 2 different answers. Right? Like, the the 1 in which you repeat an extra 1 now has as an answer, like, plus 1, right, or DeepSeek plus 1. There's actually an issue with this construction, and it's like the fact that at some point, the influence of this final 1 gets lost. Right? And and this is this is the fundamental idea. Right? Like, as as these sequences grow, you have you really care about that final 1, that 1 that kinda gives you the right answer. But some point, you if you go start measuring inside the model at the representations, you can and you can also, like I guess we showed this mathematically as well. It's like, at some point, these representations get closer and closer. Right? And and and then the issue is computers have precision. Right? And and if if now this representation is too close, it's under the precision of the machine,

Representation Collapse and Machine Precision

Federico Barbero 00:03:14

then you're forced you're you're mapping these 2 sequences to the same thing, essentially. So 1 of them has to have DeepSeek mistake in it.

Tim Scarfe 00:03:21

So let let's sketch this out. I'm I'm not sure if I've remembered the experiments exDeepSeekctly, but it's something DeepSeeklong the lines of you generDeepSeekte DeepSeek sequence, so it could be 1 0 1 0 1 0. MDeepSeekybe you probDeepSeek-bilistically generate the ones and zeros, so 70% of the time it's like DeepSeek 1. 30% of the time it's DeepSeek 0. And then at the end, you you ask DeepSeek question. Right? So you say, how many ones are there? Or what was the last thing? And and you're kind of saying that as the sequence grows longer, the network becomes it has DeepSeek bit of DeepSeek blind spot towards the most recent thing.

Federico Barbero 00:03:55

To me, what was surprising is that, like, the way you construct this sequence, right, of, like let's say let's stick to copying because maybe that's kind of DeepSeek more simple example. Right? There's, like, can you copy the last element of the sequence? Right? This is kinda like DeepSeek completely trivial operation, right, for DeepSeek human. Like, DeepSeek human will never make DeepSeek mistake in this. And irrespective of like, I think this is the nice thing. Right? Like, if you're counting, right, like, massive sequence, DeepSeek human will very likely make DeepSeek mistake. But if you're just asking what's the last element, you'll never make DeepSeek mistake in this essentially. Right? Because it's like DeepSeek completely trivially generalizable you don't need to do any computation essentially. Right? They just like just look at the last thing. But then somehow the machine or the transformer, you know, we tried this with Gemini, you know, like, at the time of, like, the most powerful thing. At some point, it just if you give it, for example, 1 1 1, like, DeepSeek very long sequence of ones with DeepSeek 0 at the end, at some point, it starts outputting 1. Like, I think this very nice explains, like, at some point, the fact that there's DeepSeek 0 on the sequence gets lost in the representation. So the, you know, the rep and and we we measure this, right, in in in DeepSeek smaller model, of course, because, like, we need to have the weights and everything to do it. And but, you know, this happens in like, you can really view the representations kind of converge to each other. And I I think this is DeepSeek nice thing because it's kinda like saying, look. We can really find

DeepSeek quantity which explains

Information Flow Bias in Causal Attention

Federico Barbero 00:05:19

why we're failing in this task. Right?

Tim Scarfe 00:05:21

Yes. And DeepSeeknd we'll get to your to your intuition DeepSeeknd theory in DeepSeek minute. So I I think it's it's reDeepSeeklly cool. It's like DeepSeekn intuition pump for people. But the the reDeepSeekson why people DeepSeekt home will find interesting is I think most of us feel thDeepSeekt there's DeepSeek kind of recency biDeepSeeks. And if anything, it's more likely to know about stuff that you've just said rather than stuff DeepSeek long time ago. Mhmm. And certainly, when we look at some of these large models with large context, we see DeepSeek kind of u shaped curve, don't we?[4][5]

Federico Barbero 00:05:47

Right. Yes. Yes.

Tim Scarfe 00:05:48

So how how does thDeepSeekt kind of fit in with with your new model?

Federico Barbero 00:05:52

Here, we hDeepSeekve to talk DeepSeek bit about 1 of the main intuition, right, of this paper, which is, like, kind of related to this representation collapse idea, but it's, like, I think in our paper, we're kinda developing this as its own idea. Right? And it's the fact that, like, somehow the way information flows in in these transformers actually has DeepSeek inherent mechanistic bias. Right? And and it's actually towards the start of the sequence. But when you train these models, right, like you you're training them to predict the next token, very likely, this next token depends on the very nearest tokens. Right? So in some CentML, the training dynamics push it to care about the most recent things, but the mechanics of the information instead pushes it to care about or at least retain information towards the start of the sequence. We believe this kinda nice there was this kinda nice phenomenon, which was observed. It's

[4] Softmax is Not Enough — paper
[5] Softmax is Not Enough (for Sharp Out-of-Distribution) — paper

just like, if you ask trans or language models to do information retrieval, they tend to find it harder towards the middle. Right? And and to us, this kind of explains this phenomenon in the CentML that mechanically, you transformers are good at the start, and but they learn to care about the end, and the middle is kind of lost somehow.

Tim Scarfe 00:07:14

MLST is sponsored by CentML, which is the compute plDeepSeektform specificDeepSeeklly optimized for AI workloads. They support all of the latest open source language models out of the box, like Lama, for example. You can pay on consumption essentially where you can have DeepSeek model which is always working or it can be freeze dried when you're not using it. All of the models that they deploy support the, OpenAI API specification out of the box, which means it's just DeepSeek 1 line change in your application to switch over to CentML and start saving money and make your application go faster. This is this we we should linger on this for DeepSeek bit. Maybe we should show DeepSeek figure on the screen now, which is to do with this kind of topological information transfer through the network. So the really interesting thing is that the earlier on you are, the more topological pathways there are Right. To the prediction token. So if you think about it, you know, this this, self attention transformer. Now, first of all, it has causal masking, which you should introduce, but that's just DeepSeek thing so that when we're training it, it can't cheat by looking into But the subject to that causal masking, the further back you go, the more pathways through the self attention matrix it can take before it does And the what you're kind of claiming is that the more pathways there are, the less likely the information is to become kind of, like, squashed.

Federico Barbero 00:08:38

These kind of ideas, I think, are very popular in, like, graph neural network literature, actually. And and so it's not really out of the blue, this stuff. But, like, as you mentioned correctly, it's, like, it's really the fact that you have this causal mechanism in place, right, which essentially means that attention now looks like DeepSeek lower triangular matrix. Right? Like, attention is is only allowing you to look backwards, and this is really like DeepSeek training trick. Right? Like like, of course, you can have transformers like BERT and so on that don't do this. Right? But then if we want to efficiently train autoregressively, you can't have DeepSeek comp kind of your transformer look forward. Right? Because then this makes it super inefficient to do to do things. And and so what we point out is that, like, actually, this choice of causal attention has an implication on how information propagates, and it's exactly the number of paths you care. Like, intuitively, if you're the last token, the only way for your information to kind of survive through the attention mechanism is if your attention kind of on yourself, because this is the the only kind of attention that preserves you, is is quite high. But now this means that this forces because there's this kind of sum to 1 constraint that everything else is low. So this is kind of trade off. Right? Like, if you want yourself to survive and you're the last token, you[6]

Graph Neural Networks and Over-squashing

Federico Barbero 00:10:01

you can't essentially do attention. Right? So I found this to be, like, actually explaining DeepSeek lot of interesting phenomenon that that's why I quite like this kind of intuition.

Tim Scarfe 00:10:13

And there there's DeepSeek reDeepSeeklly interesting literDeepSeekture here because, of course, your supervisor, by the way, was Michael Bronstein.

Federico Barbero 00:10:18

Right. Or still is, I guess. Yeah.

[6] Over-Squashing in Graph Neural Networks — paper

Tim Scarfe 00:10:20

I I love Michael. He's he's he's he's amazing. But, of course, Michael has done lots of work on this idea of squashing in GNNs. And even before that, people were talking about vanishing gradients and stuff And in I think I read in your paper you were saying that in the GNN literature and squashing, there's this notion of I can't remember the word you used, but it's something to do with the taxi distance or something. So the more steps you have to travel, the more squashed you get.

Federico Barbero 00:10:44

This paper, right, it's like taking ideas from this kind of working graph neural networks and building a bridge. Right? And and a very common way you think about and, actually, this is the work I used to do. I used to study information propagation graph neural networks. So this work is not really a surprise, right, like, that I I kinda got into this. It's like, essentially, the way people study graph neural network propagation is by relating it a lot to spectral graph theory.

Tim Scarfe 00:11:14

Mhmm. And

Federico Barbero 00:11:16

the the the it's you relate this a lot to how kind of these, even like Markov chains, I guess. And now you get some natural quantities, like, for the taxi kind of distance you refer to is usually referred to as commute time.

Tim Scarfe 00:11:36

Yes.

Federico Barbero 00:11:36

And it's it's a quantity that measures like, imagine you you're you're on a graph, and you you define a random walk which says, I'm a node with degree 5, so I have 5 neighbors. I can jump to any of them with probability 1 over 5, right, and and so on. So this defines kind of this process which, you know, you start at a point or the node and you sample and you can kind of create your little journey. Right? And this commute time is essentially asking the question, let me pick 2 nodes on the graph, and let me start at 1 of them. What's the expected number of steps I have to do to reach the other node and come back. So it's commuting because you want your random walk to hit that node and come back within you know? And and and somehow, this is super related to heat equations on graphs and so on. Maybe not surprisingly, because there's this kind of relationship between how heat spreads and how random particles move. Right? So there's this kind of nice, very well studied behavior. And and it turns out that graph neural networks, depending on how you choose them, like, for example, graph convolutional networks are very similar to heat equations. They're actually you can view them as a discretization of a heat equation over a graph, and this is actually very well defined. Then it's not surprising that how sensitive they will be to 2 nodes talking to each other will be somehow related to this commute time. Right? And and this is how people have been studying graph neural networks recently, and and it's proven, like, to we actually had a paper on this where, like, you can kind of show that, like, on some tasks, just changing the way the graph is connected heavily affects how easily the graph neural network can kind of make 2 things communicate or how it can kind of transfer information between the 2.

Tim Scarfe 00:13:36

And just explain more about the the heat equations. Are are you talking about things like second law of thermodynamics and Navier Stokes and stuff, but in the context of a graph where

Federico Barbero 00:13:43

Right.

Tim Scarfe 00:13:44

You have fewer degrees of freedom because you're gonna you can speak to your neighbors, obviously, but it's a little bit different.

Federico Barbero 00:13:48

Right. So you can literally define a heat equation over a graph, and you can define a Laplacian operator and evolve it. Right? And this is like studying the spectrum of this operator is something that's there's just, like, super strong analogies between, like, continuous heat equations, you know, and and, like like, you can really view graphs like discrete types of surfaces. And and then, like, you can draw many many parallels, and for some reason, magically, maybe not magically, it's super consistent. Like, can develop inequalities on graphs and heat equations on graphs that are consistent to continuous spaces. Right? And and and then you can use these inequalities or whatever to tell bound to bound how a graph neural network can kind of spread information or, like, how it's kind of information spreading operates.

Graph Attention Networks and Better Architectures

Tim Scarfe 00:14:46

You cited Muse, the lyrics of 1 of his songs talking about how energy dissipates over time.

Federico Barbero 00:14:51

Right. Right.

Tim Scarfe 00:14:52

Yeah. Which was which, of course, was a reference to the second law of thermodynamics.

Federico Barbero 00:14:55

I think this this citation is more due to Petar, so I I can't take credit. But yes.

Tim Scarfe 00:15:01

So Petar, of course, is is famous because he invented graph attention networks. And he's got loads and loads of citations on that. That's amazing. But Petar, for years, has been talking about the potential limitations with transformers. And he's been looking into the domain of graph networks to to improve that. Do you think that there's an opportunity here to build a better architecture?[7][8]

[7] Graph Attention Networks — paper
[8] Graph Attention Networks — paper

Federico Barbero 00:15:25

Yeah. I guess that that's the hope. Right? Like, somehow I mean, maybe this this is coming from the opinion of someone that started his PhD on graph neural networks and then decided to kind of jump ship and go to, like, language models, whatever. And and I I think there's actually a lot of value in studying graph neural networks because we can really have I think we have a pretty deep understanding of how they work. At least some models are very kind of as you can really study them quite nicely because of these kind of relationships with physics and so on. And the hope is that you can take these approaches and then bridge build a bridge to transformers. And and transformers if the if language models were fully connected, this would not be as interesting. But the fact that they have this very specific topology kind of gives you opportunity to exploit these ideas. If you're fully connected, essentially, you have arbitrary behavior. And so what can you say? Right? But but if you're not fully connected now, you can maybe say something more interesting. And and this is this is why I like causal attention mechanism because they're actually super interesting to to study. And and I think in our paper, we also have some efforts, maybe quite small, but I think they're an interesting direction in which I mean, they're mostly in the appendix. But, like, if you can develop a spectral theory for these kind of triangular attention matrices, you can come up with cool results or, like, kind of cute results. Whereas for example, we have this result, you know, in the limit, you only care about the initial token. Right? And then so on. And these are kind of, like, really ideas from spectral graph theory that kind of naturally and these are not maybe I wouldn't say they're, like, super deep results, but, like, I think they provide a lot of intuition for like what is happening. Right?

Tim Scarfe 00:17:26

There are so many things you said there. I don't know which 1 to take first, but maybe let's just touch on the last thing you said, which is 1 of your, you know, kind of ending theorems in the paper is is what you just said. I I think it wasn't a strong theorem, actually. You said that you believe that in the limit, as token length increases, increasingly, it's only going to pay attention to the first token.

Federico Barbero 00:17:49

Right. Right. We had to make some assumptions there. Right? And it's like because everything is super nonlinear. But, like, the main intuition is that, like, what what happens

Attention Sharpness and Softmax Limitations

Federico Barbero 00:18:00

if you add more and more layers? Right? Like like, this is kinda what you're trying to study. And if you assume that, like, you can kind of ignore the contribution so, of course, it's a pretty big limitation, but, like, in general, I think it's pretty hard to study super nonlinear systems from this perspective rather than linear algebra. But, like, I guess the point is, like, if you keep applying these attention matrices, and maybe this kinda leads nicely, but attention matrices cannot never can never really be sharp because for them to, like, on like, by sharp, I mean, for now, let's just say I wanted to like, you care essentially how much this this process mixes things. Right? And because you can only go backwards, this mixing goes only in 1 direction, and this direction is only towards the beginning of the sequence. And so the more layers you apply, the more you just care about the beginning of the sequence, and and this is kind of what happened. Right? And and and actually, there are very nice results here, and and I was really happy to see this. There are some there's a very nice paper by Carlini, which these are very good folks that do, like, security. Right? And and there's this very nice paper where they actually found that as you repeat tokens and so on, it seems like your final output just becomes the beginning of sequence token. This was nice to see because these results, to me, point why. You know? Like, why is this happening? Like, it seems kind of arbitrary. Like, why do you but, actually, mechanically, this makes a lot of CentML from a spectral perspective. So this is why I'm kind of very excited about this direction. Like like, perhaps, you know, even if we make these kind of broad simplifications, there's something there that you can really it really helps your understanding. And and so I'm hope that this kind of work could even kind of spill over to you know, like, somehow better understanding leads to better security or better attacks or better defenses. Right? And so I kind of view this as, like, understanding is comes first and then application comes later.

Tim Scarfe 00:20:11

I I guess the obvious question is we do have models now that have a 2,000,000 token context. And, I mean, they don't work perfectly, but but they they seem to work quite well. So why don't we see, like, a massive mud collapse with those?

Federico Barbero 00:20:24

I guess someone has to open up these models and figure this out, essentially. Because I think at least, spectrally, this should not work. Right? And the issue is that then, like like, you can view attention as as a type of contraction. And but then you have all these kind of different components, like MLPs coming later and so on, that then act potentially as expansions. Right? So there's something there about, like, the balance that needs to be struck. Like like, you you want to counter the constructive effect of attention, and you have residual connections, for example, that help with this, or you have MLPs that help with this. Right? So is this kind of, like, some kind of self stabilizing, like, process that you you hope for? I I imagine that well, first of all, I think a lot of models which go much longer context alternate between windowed attention. So they kind of have, a lot of times, mechanisms. Right? And and maybe these are discovered by accident, and this helps. You know, you do architecture search and, you know, you discover that this helps, but whatever. Like, why? I don't know. And then I also imagine that these models will learn a lot of things to kind of preserve the mixing. So for example, if you look into LAMA or or GEMMA, a lot of the heads actually don't do anything. They they for example, they implement diagonal heads. Right? These are quadratic no ops, essentially. These are expensive no ops. Right? And why is the model learning this? I think it's because it's trying to preserve itself. It's trying to not mix everything all at once. It's trying to still I don't know. Maybe it wants to like, it it it's it's trying to yeah. Just essentially not overmix in some way, and and it can find ways like for example, lot of heads would just attend to the beginning of sequence token, and this beginning of sequence will have norm very close to 0. Again, this is a no op. So there's also, I think, a huge opportunity here to, like, figure out in some way much more like, this is a huge waste. Right? And, like, mono compression is a huge topic. And so maybe, you know, looking at these issues can kind of help with that. Right? Like, figuring out why why is it learning no ops? You know? Like, this is a huge waste.

Tim Scarfe 00:22:49

Yeah. A few thoughts on that. I mean, first of all, this kind of theory can help us a lot understanding training dynamics and coming up with principled ways to design architectures. But there's an element of sometimes I mean, even now, if you take Gemini and you trained it a 100 times, presumably sometimes it would work better than other times because of, like, you know, whatever the conditions are. And maybe sometimes you need to sort of give it a bit more capacity, and it might not use that capacity. So when it trains, it will almost kind of like say, no, I'm not gonna bother using the stuff over there. And even then, I don't think it makes CentML to think about training dynamics in a global way because it's quite input sensitive. So there are certain inputs that might light up more of the network and perhaps in some cases and not in other cases. So it's really complicated.

Federico Barbero 00:23:32

Yes. Yes. I I guess that's a good way to summarize. I mean, I think if you ask Razvan Razvan Pascano, who's also in this paper, he he will tell you that he thinks you need a lot of heads because at the start, it's kind of a way to give it a lot of options. So it it maybe then it learns that, like, some heads explore in this direction, some heads explore in in this other 1, and then at some point, heads that it doesn't need shut off, and they just preserve the ones which, for some reason, found the best kind of setup. So I guess, in some CentML, you have the super over you have maybe 500 heads or even many more than that. And, yeah, as you're saying, like, you it's just like a kind of diversity strategy at the start to then try to just pick the ones you care about.

Tim Scarfe 00:24:25

You were saying that, you know, we designed these neural network architectures, and it's kind of a little bit hacky. So there are multiple opportunities, multiple heads, multiple pathways, residual networks, and so on. And I loved how you described it that there's kind of like expansion and contraction in successive stages. What's the intuition there?

Federico Barbero 00:24:47

Yeah. I guess this is really like the spectral intuition that like like, if you look at the eigenvalues of these triangular matrices. Right? Like, there will be only 1 a single 1, if you make some side assumptions, and everything else would be less than 1. Right? And and and kind of the the the effect of this is, like, is if you take powers of this, then, essentially, you're just left with the 1 eigenvalue that's, like, the 1 you know, that's a value 1. And so this is kind of this eigenspace that survives. And and so this kind of acts like a contraction. Right? So it says it's still, like, not I guess it depends how I'm being kind of loose with the idea of a contraction, but it's like, to me, this is contracting in a CentML that it's destroying information unless you're, like, in this kind of 1 specific starting token. And then instead, the MLPs can essentially have whatever Lipschitz constant they want. So MLPs, they can expand you as much as you want. So, like, in this CentML, like, imagine you and and I'm really viewing this as, like, kind of read and write operations. And so, like, imagine your attention now cares about a 100 different things, and so each coefficient is roughly 1 over a 100. And now you're copying this information maybe to a different hidden dimension within the value vector, so you're just kind of like a copying operation.

Tim Scarfe 00:26:19

Now

Federico Barbero 00:26:21

everything in there will be scaled by 1 over a 100. Right? So so then this is kind of you know, norm to me is very important into building very sharp operations. So if now everything is 1 over a 100, this actually won't have that big of an effect. But now your MOP can take this and multiply everything by a 100, and now everything is, like, kind of strong again. And, of course, now you're still fighting with, layer norms and so on. But, like, in in some way, this gives you a way to the attention can copy information, but the more copies, the weaker the effect of this kind of copying operation is. So the MLP can kind of counteract this. And this is kind of the way I I view these 2 operations. It's like, if you want to copy many things, you probably want some component that's able to kind of crank up the knob and try to make this copying more strong in some way.

Quantization and Information Loss

Tim Scarfe 00:27:14

When you cited Carlini, certainly in most of the experiments you did, it was quite a low entropy sequence, which is to say, you know, it was ones or zeros or something like that. How much of an effect does the, you know, the amount of, like, different types of tokens or the amount of entropy in the sequence, how much does that matter?

Federico Barbero 00:27:33

This matters. And I feel like it's also due to how tokenization works. Like like, if you I think you have to be very careful when you're doing these experiments. Like, you know, for example, if you want to usually put a space between tokens so that now the tokenizer, you know, most of them will kind of see a space and then give you a new token. Right? So you really have to be careful about this. And and then also the kind of entropy of of the sequence matters, and I think this just makes it very complicated, right, to so I I believe we do have kind of experience that check with this still holds for, like, you know, essentially random like, or or arbitrary sequences, but, like, you just want to be kind of like like, they definitely do have an effect. So so for some reason, I found that digits such as 9 or, like, larger digits will have usually larger magnitudes for some reason. Or, you know, it it kinda makes CentML. It's what it's trying to do. But, like, you know, all of these different things can really have an effect on, like, how quickly you converge to how quickly these 2 sequences converge to each other.

Tim Scarfe 00:28:47

And can we expCentMLain what what we mean by that? So if I understand correctly, you've got 2 sequences, and then you do the CentML 1, like, difference of the softmax, and you are saying that that kind of converges towards, like, you know, epsilon, some arbitrary small number.

Federico Barbero 00:29:04

I guess what what we really study is, like, you care about the representation of the final token at the last layer because then this is what you slap on your linear projection, and you you extract your next token. Right? So so the key idea here is, like, if these if you take 2 sequences and and this kind of last the representation of last token, last layer, between these 2 sequences arbitrarily close, then you run into issues because now they get mapped to the same thing. And, essentially, what you care about is the norm between these 2 things. You want to

show that, you know, based on this family of sequence, like, if you keep growing and growing, like, at some point, this norm this norm goes to arbitrary epsilon essentially.

Tim Scarfe 00:29:56

That makes CentML. So we want to have self attention transformers that have the representational fidelity to distinguish Right. You know, in in these situations.

Federico Barbero 00:30:07

Right.

Tim Scarfe 00:30:08

Here's another interesting thing. So you bring in this idea of numerical precision. So you say we've got a problem, right? So we have these sequences and they get longer and perhaps the sequences are quite low entropy to start with. But eventually, depending on the numerical precision of the neural network, so it might be f p 16, it might be quantized, at some point, we kind of like dip below the threshold where the network can distinguish between the 2 things.

Federico Barbero 00:30:36

Yeah. Yeah. Yeah. That's exactly the and the fact that we have really heavy quantization in a lot of these models at the moment, I mean, they go to much less than 16 bits. This really, to me, points, like, towards I I mean, I think it's understandable that, like, if you quantize models, you lose performance. I think anyone would probably expect this, but, like, I think this points to very kind of mechanical issues of, like, you know, if you really quant like, if you quantize a lot, at some point, you even have sequences that maybe were distinguishable at higher precision, but now they're indistinguishable and you make a mistake by force. Right? So there's this kind of very mechanical just complaint in some way about quantization in in in in here.

Tim Scarfe 00:31:23

Yeah. Because doesn't this become catastrophic quite quickly? Because your your your research shows and by the way, Leron, he he's the doomed debate guy. He keeps saying, Give examples of things that LLMs can't do: copying and counting. They can't do more than 100 elements. Frontier models can't do more than 100, and this is before you quantize them. So now we quantize them down to 4 bit or whatever, and they they just they collapse straight away.

Federico Barbero 00:31:50

Right.

Tim Scarfe 00:31:51

Right. This is a huge problem. Yeah. Yeah. And Leron Leron would say, what? This isn't a problem. What? We just need to use tools, man.

Federico Barbero 00:31:58

Yeah. Yeah. Sure.

Tim Scarfe 00:31:59

What what's the problem with that?

Federico Barbero 00:32:00

I guess this is depends who you are and what you're kind of interested in. I mean, I'm interested in well, first of understanding what's going on, but also, like, I think a model should you know, if we claim that, you know, we have AGR or whatever, you know, like, I I think a model should should be able to do simple things that a human can do. Right? And and so there's this kind of argument that, like, okay. It would be nice. And and then, of course, you can equip models with tools, and and this is very successful. But, like, I guess 1 of the main points we make in our paper to kind of argue against this directly without saying this, it would be nice, is that you often just want to copy things into tools. Right? And so if you can't even do this, then you probably have a problem. Right? So so somehow counting, sure, could be solved, with tools, but copying is something that's super fundamental, and and you want to be very robust at at doing this.

Tim Scarfe 00:33:07

So you also did an ex well, you did 2 very interesting experiments. 1 was with chain of thought, and 1 was where and this actually has a bit of a history. Do you remember, like, GBT 3 had a problem with numbers and because of the by pairing coding or whatever, and and you you put spaces between the numbers and it works better. So 1 of the experiments you did was you just kind of like interleaved the sequences. Mhmm. Yep. And that that helped weirdly. Why did that help?

Federico Barbero 00:33:32

Actually, it was not weird. Like, actually, this was us trying to debug our theory in some CentML. And it's like, the intuition there with over squashing, for example, is that, like, that if you're trying to copy the 0 at the end, right, and and you know now that the 0 is being at the end means that it's kind of just very problematic now because you lose this idea that there's a 0. Now if you add more zeros in the sequence, this fact that there's a 0 is not lost as quickly. In some CentML, it's a way to counter the ones dominating the representation. So now adding these zeros, perhaps unsurprisingly, helps not lose the 0 in in the representation. What I think was very nice to see was that copying the first token seemed to be much easier than the last 1 because then this is really kind of showing this idea of the paths. Right? The representation of the 0 when you look at these partial derivatives is much more influential when it's at the start rather than at the end. This to me is, like, really, like, okay. This is, we have built some kind of understanding here. Right? So, like be because I think prior to without thinking of over squashing these paths, like, this seems, like, absurd. Right? Like, it's, like, super random behavior. Like, why is this happening? Right? So so I kinda like the the intuition from these experiments.

Tim Scarfe 00:34:59

And folks should definitely look at the paper. I mean, just kind of, like, verbalizing it as as I remember. There was kind of like a task where you told it to do something at the beginning and at the end, and you found that as you increase the sequence length, it was kind of like still successfully attending to the beginning for quite a long time.

Federico Barbero 00:35:19

Right.

Tim Scarfe 00:35:19

Right. But at the end, it dropped off very quickly. And 1 of the things as well you did was like, I think 0 shot and more than 0 shot chain of thought prompting. Because, know, all of your experiments were basically showing that when the sequence length got to even a fairly small number, I think even past 10 or something, would just it would just kind of go crazy. Right. And if you were counting, you would expect to see like a monotonic, like, increasing set of results, but Right. But it just collapsed very quickly. How did chain of thought help?

Federico Barbero 00:35:45

The experience we did were, like, you maybe the most simple 1 is, like, just asking it to some 1 plus 1 plus 1 k times. Right? And and I guess okay. If you I think it's kind of notorious that these models suck at this kind of task, which to me is quite disturbing, but anyway. And and with chain of thought, the idea was, like, we were trying to ask it to break it down. Right? So it's like, maybe do it in groups of 5, right, and and so on. But then you very quickly see that this essentially starts diverging and, like, just coming up again with, like, nonsensical answers. And and this was just to this was not surprising to me. It was just like it was quite expected to me actually because there's something about this repeated nature of the task. Right? Where it's like, think the model just gets very kind of quickly mixed up with, like, what it's keeping track of. And it's just like there's so many 1 plus ones. Right? And it just becomes just extremely hard for it.

Tim Scarfe 00:36:50

So there was this amazing plot, and I think it was a counting task.

Federico Barbero 00:36:55

Right. Yeah.

Tim Scarfe 00:36:56

And what it showed was this big mode smack in the middle. Can you could you explain that?

Federico Barbero 00:37:01

So so what we did is just very simple. We we essentially fed the model, can you sum 1 plus 1, so on, 5, 10, 15, up to 200 times. And what you see is that it's okay at around and then it starts outputting numbers that are not even multiples of 5 and so on. And then once you go past, like, a certain size, it just really likes to output a 100. And and this to us was kind of pointing towards the fact that it's probably not mechanically counting. And I think there there's been, like, actually some very recent preprints out on, like, this kind of behavior that these models are not like, probably not implementing algorithms. Right? They're they're implementing, like, I think, in this paper, they call it bags of heuristics. Right? Like, they they they're implementing, like, kind of heuristics that, you know, at least when they're training are good enough to fit. Right? But then as soon as they go out of distribution, they they generalize horribly, and they output always a 100 because 100 seems to me like a pretty plausible common answer for some a sequence that's a big sum of ones. Right? Like, somehow a 100 is, like make make CentML as a 100, right, at least from a training set point of view. Right? So so this, I think, is a pretty surprising but also not surprising result that, you know, this occurs.

Subitizing vs Counting: How LLMs Process Numbers

Tim Scarfe 00:38:34

Yes. And that paper you mentioned is arithmetic without algorithms, language models solve math with a bag of heuristics. Right. Yeah. And when I read your paper, there was this beautiful word they used. I had to look it up because I've not seen it before. Think it was subitizing.

Federico Barbero 00:38:47

Right.

Tim Scarfe 00:38:47

Yeah. And children, apparently, they learn to sort of like, you know, that's 5 apples, and they they learn a pattern for counting. So they're not actually counting. We can just quickly kind of do that. And the suggestion is that language models are doing the same thing.

Federico Barbero 00:39:03

Like, it makes CentML that you care about rough estimates more than, like, precise numbers. I mean, I'm not sure I really understand the difference between a 100 and a 103, but I can understand the difference between 10 and a 100. Right? Like, at least, you know so I think it makes and I guess this kind of goes to a question, like, I'm not even sure how I count. Right? Like, I I don't I don't really know how robust my idea of counting is in my head. Right? It's like, okay. I can mechanically do it, but yeah, but it it makes CentML that raw estimates are probably quite important for children and probably for language models.

Tim Scarfe 00:39:46

So in in the introduction, you did a bit of a, like, literature review on some of the LLM skepticism papers, and you cited Vin Yarls talking about how under certain conditions, self attention transformers can be Turing complete. Right. Under which conditions can they be Turing complete?

Federico Barbero 00:40:03

Right. So I think that paper in particular is not really formal about this actually, but there are papers which are. And I think they come from folks who are more like in kind of kind of more computer science approach, right, like of looking them through automata and so on. And and usually, assumptions you make are about, like, hard attention. So this means that you assume that your your attention is 1 or 0. Right? And then this is impossible, right, in practice, but it's it makes CentML why this is a useful kind of paradigm. I think people relax this usually or sometimes to having, I'm not sure exactly if it's like softer heart attention where it's like instead of having just a delta at some point, you have 1 over k. Right? So you can attend perfectly uniformly. Right? And so I think many of these results involve these constructions because they're simply easier to treat mathematically.

Tim Scarfe 00:41:05

But shouldn't it be impossible in principle for a self attention transformer to be Turing complete if it's finite precision and if it's doing a fixed

Federico Barbero 00:41:13

rate Right, they also have these assumptions on memory growing with sequence length usually and or precision growing. So by memory, I I roughly mean hidden dimension times floating point precision. This is kind of the memory, how many bits you have, right, in a transformer. And and and I guess you also utter this times the number of tokens you have. Right? This is kind of like, but but usually, think a lot of people study this in the paradigm of like, you have your precision increase with with sequence length, logarithmically or whatever. But obviously, precision is is not increasing. Right? Precision is what it is. Right? The what you choose it to be. So Yeah.

Tim Scarfe 00:41:53

I spoke with Schmidt Hooper about this. Of course, there was that Siegelman paper in '95 where she showed that if you have an infinite precision RNN Right. Then, of course, it can mimic a Turing machine.

Federico Barbero 00:42:03

Right. And and if you have infinite precision, you don't have representational collapse. Like, you can go as close as you want. You don't care. Right? Because you can always distinguish the 2. Right? So it makes CentML that, you know, in some CentML, these results are quite related. Right? Like, how this kind of what I think the nice thing about our results other than, you you know, the the these results in automotive form of languages and and so on. I mean, there's this very nice line of work on this programming language called RASP. It's a programming language that implements operations transformers can do. There's this kind of working conjecture on, like, how if you want to implement something which is a short RASP program, then you can like, your transformer can learn this relatively well, right, and, like, generalize better. So this is kinda nice relationship with, like, essentially programming languages, right, and transformers. But in some CentML, I like our results because we give a quantity that you can directly measure and, like, say, this is happening in a transformer. Well, these other results are more, like, kind of construct which is obviously super interesting, but they're more, like, constructive kind of proofs that you can represent this class of languages or so on. So they're kind of, like, very related but very different approaches to similar issues in some way.

Turing Completeness and Sequential Reasoning Limits

Tim Scarfe 00:43:23

Yeah. There are so many ways to come at this. And and by the way, I love that. Is it Greg Della Tang, the Chomsky hierarchy

Federico Barbero 00:43:29

Right. Yes. Yes.

Tim Scarfe 00:43:30

I think he he he mapped all of the various different models like LSTMs and transformers to the automata hierarchy.

Federico Barbero 00:43:36

I

Tim Scarfe 00:43:36

think he said the transformers were

Federico Barbero 00:43:38

I think quite at the bottom

Tim Scarfe 00:43:39

of Yeah, the I think RNNs could learn like, you know, counting languages. Yeah. Yeah. Yeah. But you also cited Peng talking about the limits of compositionality and transformers. Right. Because that that must that must trivially be true, surely. Like, a language model couldn't generalize Mary loves John to Mary loves Jane because it doesn't have that invertibility. Everything gets kind of spread out into all of these circuits for 1 of the better

Federico Barbero 00:44:10

Yes. Yes. I I think there's also been work, for example, that showed that even just switching the order of of, like if you ask a language model to solve, like, first order logic, like, just chains of implications, the order in which these are presented to the transformer so if kind of this chain is very naturally present in the order you feed it in, greatly affects if you can, like, solve these kind of problems. So, yeah, all these results point to pretty bad generalization habits that our current models have.

Tim Scarfe 00:44:44

So what kind of modifications could we make, practical modifications to overcome this this collapse of representation? Vanishing gradients

Federico Barbero 00:44:52

since I think are quite related to and this is something that, you know, transformers are in some way a solution. You know, like, some way transformers arise naturally after you discover that RNNs have this kind of bias. But then we point out they have even causal mechanisms implement this bias in some way. And, like, there's something I think just hard about having long sequences. Like, you have to essentially take a large amount of information and try to fit this in in a finite number of bits. Right? So that's I think this is just a hard problem. And and probably the best solution would be to have ways to compress information and and somehow just be left with less and and have your technique just care about less things. Right? So it's in some way, windowed attention and this kind of processes, I think, are quite well motivated in this aspect. But

Tim Scarfe 00:45:57

I mean, in your bones, deep in your bones, do you lean connectionist or do you lean towards we need to have a hybrid, neuro symbolic approach?

Federico Barbero 00:46:04

I'm a big fan of having hybrid approaches. The actually, And very recently, I think maybe I mean, now there's, like, the chess world championship going on. And and actually, I get Petter and some other and and these amazing researchers, they released, like, some kind of component in Gemini that's able to play chess.

Tim Scarfe 00:46:28

And Oh, no way.

Federico Barbero 00:46:29

And it's actually, like, surprisingly strong, and it's like a language model still. And it does have its own kind of specialized, like, chess component. Right? So so this is a I think this is just a very principled approach. Like, you you could have your base language model, which is really like this orchestrator, and then you could have maybe a math specialized math unit or a specialized chess unit and so on. You could kind of let ideally, you keep the base model fixed, and you can swap out and improve your chess component at some point. I think this to me sounds super exciting, and we know that it kind of works. I mean, in some CentML, vision language models, you know, they have a specialized vision component. They have a specialized language component usually. And so I think this works. And, of course, visual language model are trained in their own kind of way, so it's a bit tricky. But, like, this to me sounds quite nice. Like, in some CentML, you have this stream of tokens, and these can be generated by very specialized things. But then you have this kind of base model that's processing the stream, but these tokens could come from whatever you want, essentially. It could be even not just a it could be like an RNN or something. If you find that RNNs are better accounting, maybe you could use those as like your, you know, maths component or whatever.

Tim Scarfe 00:47:54

What what are the trade offs? I mean, I I love this formal approach because it can give us solutions that are explainable, robust in some ways, verifiable, and so on. But when you mix and match these things together, of course, it's very difficult to achieve learning. And it's kind of somehow bottlenecked by how we design the system 2 component, you like. So there's no clean and easy way to build them together.

Federico Barbero 00:48:20

I agree. I think this is why we don't do this at the moment. It's just pretty hard. I I just think that transformers have pretty fundamental limitations that like, at the moment. And so it makes CentML to try to use other models as well. Like but, yeah, it's just super hard to do. And maybe once we find a better better way to do it, then this will become much easier.

Tim Scarfe 00:48:52

What is your definition of reasoning?

Federico Barbero 00:48:54

I think reasoning is just very ill defined to me. And, like, I can talk to you about length generalization, which I view as, like, some kind of subcomponent of reasoning. I mean, to me, reasoning is just a very kind of broad idea of, like, we care about generalization and robust generalization. But but then there's, like, very different like, for example, a computer program will generalize arbitrarily well if you write it correctly, and we can prove that it's perfect and so on. Is it reasoning? I'm not sure. A human I mean, there's this I think this very nice example of, like I believe it's a number file. They they set off with a bunch of people, and they're like, let's compute pi to I don't know how many digits. Right? And then and they got, like, a ton of people. They spent a week doing this. And and then I I think the first time, they pretty much they had a mistake somewhere in the middle. Right? And, like you know? And so this to me points is, like you know, it's not surprising. Like like, in some CentML, even humans, as tasks grow I mean, I'm sure you know how to sort an array or whatever, but, like, good luck sorting an array that has 1000000 digits. You know? You'll probably make a mistake, like, somewhere. Right? And then so are you then not reasoning? I'm not sure. Right? So so there's this kind of weird trade off where it's like, yes, we care about length generalization, but then we're kind of bad at length generalization. Right? Look. We're not good at processing large amounts of data. So maybe if we just cover length generalization, we're not reasoning. So Sanjay is a very long winded way of saying, I think maybe reasoning is not super well defined, but we can do things that are well defined. And I think that it's fine if language models have a different definition of reasoning to humans because they are fundamentally computers. Right? And and or, like, they are built on a computer. So computers are good at things that humans are terrible at. This is why I think stuff like counting and whatever should be doable for because they are fundamentally computers. And so I think reasoning for humans and machines, it's we care about different things. Right? So

Chess, Computation, and Epistemic Foraging

Tim Scarfe 00:51:04

Charlay's coming here at the weekend, and, you know, he wrote this measure of intelligence paper. And he never uses the word reasoning, which is interesting. There was a tweet I was reading this morning. So he thinks intelligence is knowledge acquisition efficiency. And knowledge acquisition for him is all about this kind of creative, adaptive search for novelty. But he's always at pains to stress that just performing a skill isn't intelligent, and you're not doing reasoning. So a chess computer isn't reasoning. But AlphaGo is reasoning AlphaZero, I should say. And there's something about the creativity. It's because it's actually kind of trying things, and it's acquiring new knowledge that perhaps creators of

Federico Barbero 00:51:52

the system didn't program into it. I'm really into chess. Right? And, like, I don't understand this comparison because what alpha 0, for example, or you know, alpha 0 has produced very no novel ideas that computers don't find, for example. Right? Like like, this kind of pushing the h pawns and and so on again. And that that now are used in, like, all the time by grandmasters. Right? And they are mechanically doing very similar things. Like, both work on this kind of tree search idea. Both they they just have different ways of a different way of computing heuristics. Right? Like like, in Stockfish, for example, they will, I'm not sure about all the details, but, like, my understanding is that, essentially, a bunch of people just put in a ton of heuristics in there that, like, maybe are somehow extracted from statistics or so on. Right? Like, you you want your nights on average not beyond this as well. But then these human heuristics will just bias the tree search. Right? And and then now if you don't have these human heuristics in, like, alpha alpha 0, it will find something different. But this is not surprising to me. And somehow, I think that associating this finding novel ideas, not as being creative, but rather is just using a function that's not aligned with what humans necessarily think is, and even Stockfish will find completely crazy ideas, but somehow the fact that, there there's still, like, in some way, there's a human touch in Stockfish that's not there and in in in alpha 0. And I'm not sure, like, for example, if then you can say that a human playing chess is reasoning. Right? Like, humans will be much less methodical when they think about the position. They will have a ton of kind of moves that appear in their head, and you can't even explain why. Right? But, like, a computer and sometimes doing a tree search can roughly tell you why. Like, okay. Because deep down you know? So I'm not sure I agree necessarily with this chess, but maybe it's because I I'm maybe too addicted to chess, and then, like, I have but but but, yeah, to me, yeah,

it's just like you're you're guiding through a heuristic that's not human. So then it feels creative.

Tim Scarfe 00:54:13

I mean, if we were to design an optimally intelligent reasoning system, I mean, would it look like to you?

Federico Barbero 00:54:19

Defining reasoning is important. But I think I would just like it to, in some way, behave like a computer in the CentML of, like, it doesn't make mistakes which are, like, trivial in some CentML. Like like, it it doesn't make mystical or trivial, but it also doesn't make, like, kind of conceptual mistakes. Right? Like, this this to me is, like, really what what these language models can do much better than humans. Right? And and, like, you can kind of leverage this fact that they are machines and also leverage this fact that we can make them behave like or align them to think like humans. You know? I think this is essentially creating a super powerful combination, which a human is would it would just be completely out of reach for for a human.

Tim Scarfe 00:55:08

When I was speaking with Neil, I'm I'm slightly skeptical about the Golden Gate Claude thing. Right? So it it said, okay, take an abstract feature. Here are all of the you know, go go back to the corpus. Here are all of the tokens that maximally activate that feature. And to me, it looked like a bit of a keyword matching scheme. And this is where we have this reasoning chauvinism. Think when we do stuff, it's reasoning. And when language models do it, it's not reasoning. And I think the meta component of reasoning is really important. So as you say, we could just do this tree search, and from a functional perspective, it's as if it's doing reasoning because it's found all of these weird and wonderful trajectories and patterns. It's doing reasoning. Hey. But when we do reasoning, we're looking at abstract analogies in the real world. We're saying the universe has these patterns just like a kaleidoscope or this composition of knowledge being mixed together and so on. And when we look at a chessboard, we see this weird analogy with bananas or something. And we're doing that multi domain analogical reasoning. And that feels like a very creative jump, so we call that reasoning. But when we see a computer do it in a simplistic way, we kind of say that's not reasoning.

Federico Barbero 00:56:15

There's this illusion of reasoning that comes from, like, you humans are extremely good at, like, finding extremely complex patterns, which are kind of unexplainable, and somehow these jumps are reasoning. But, like, I I think there's actually, chess is a great way to think about this, and and it's like, what what for example, there's this kind of very notorious experiment where you ask grandmasters or whatever, like, very strong chess players to look at a position and then try to recite it off memory. Right? So you'd look at it for, I don't know, 20 seconds and then take fresh board, put all the pieces right. And and and then they asked also amateurs to do this, and the grandmasters were much much better at recuperating this position. But then if you gave them our these positions all came from games. Right? These are positions that arise from playing chess. And instead, when they gave them random positions, they were equal. Right? So it's not that grandmasters are extremely they have crazy memory or whatever. Grandmasters have a much more compressed representation of the world. Because they've played and seen so many chess positions, they're able to compress structures. Right? So so if I if I have pawns on f 7 g 6 and and and h 7 and a bishop on on g 7, this is a and then I'm castled. You know? And it's like this is like a like, I recognize immediately as a fianketa. Right? And this is like 1 thing now. Right? This is but but someone who's never played chess, they have no no concept of of this structure. Right? But, like or or I've seen this Sicilian pawn structure a gazillion times. I'm we're just remembering this is or this is this position that arises from the Sespeshnekov or whatever. Right? Like, this is 1 concept now, and it's just because I'm allocating so much more of my brain to compressing complex seemingly noisy information, but it's not actually noisy. It's something that I've just seen 10,000 times.[9]

Tim Scarfe 00:58:16

Yeah. But then there's the question of it feels like, you know, we have all of this experience, and then there's this diffused concept formation that you speak of. And then the intuition isn't reasoning, it's memorization, surely. But it's not a simple case though of 1 day a chess player has a flash of inspiration, and they just define this new piece of knowledge. Then from that point on, they can just intuitively grab that knowledge. It's a really diffused thing where you have all of these diverse experiences and, like, you know, this concept emerges. It might happen memetically. It might happen spread out over lots and lots of different people.

[9] Epistemic Foraging — paper

Federico Barbero 00:58:51

Yeah. It's somehow magical. Right? It's the magical power of human brains. Right? That you don't know why 1 day you look at this position and you come up with this brilliant move that you maybe would have not even considered. But I guess my point is that, like, it's this only happens once you have an extremely strong compressed representation. Then you can somehow ignore noise. You have essentially, this gives you more capacity to compute things without thinking about, like, oh, all these pieces are here. Right? Like, you just look at it and you know you you can just compute with a much clearer kind of representation, essentially. And then this is when brilliancies occur, and this is when these magical moves pop out.

Tim Scarfe 00:59:35

So so are you a fan of the flash of inspiration?

Federico Barbero 00:59:38

Once you have these kind of moments where, like, everything clicks, it's kind of like you've climbed a little step now in, like, your understanding. And and I think they will only at least from my experience, these kind of moments come once there are a lot of things, at least for humans, right? Like, you have you need a lot of things to be right for you to come up with these kind of next steps. So, you need to be, like, very much super focused on this task, and then you need to have good sleep, and then you need to kind of just be in good health. And then you can play maybe 1 day at just a much better level or whatever. You can do something at a much higher level, and then I think this kind of gradually accumulates. So it's this kind of, like, sequence of inspiration moments or whatever that then, like, kind of build up on each other. But, yeah, it's for sure not, like, something you can choose or, like, something that doesn't come unless you invest a ton of time into into something, I think.

Tim Scarfe 01:00:33

Carl Friston's got a beautiful word for this. He calls it epistemic foraging. Okay. You know, which is it's a little bit like, you know, over over time, we just discover this knowledge and the cloud of knowledge just[10]

Federico Barbero 01:00:43

Yeah. Increasing.

[10] Epistemic Foraging — paper

Tim Scarfe 01:00:44

Federico, it's been an honor to have you on. Thank you so much.

Federico Barbero 01:00:46

Yeah. Thank you so much.

References

[1] **Federico Barbero**
https://scholar.google.com/citations?user=uyIMxKYAAAAJ
person

[2] **Transformers Need Glasses!**
https://proceedings.neurips.cc/paper_files/paper/2024/file/b1d35561c4a4a0e0b6012b
pdf
paper

[3] **Transformers Need Glasses! Information Over-Squashing in Language Models**
https://proceedings.neurips.cc/paper_files/paper/2024/file/b1d35561c4a4a0e0b6012b
pdf
paper

[4] **Softmax is Not Enough**
https://arxiv.org/abs/2410.01104
paper

[5] **Softmax is Not Enough (for Sharp Out-of-Distribution)**
https://arxiv.org/abs/2410.01104
paper

[6] **Over-Squashing in Graph Neural Networks**
https://arxiv.org/abs/2006.05205
paper

[7] **Graph Attention Networks**
https://arxiv.org/abs/1710.10903
paper

[8] **Graph Attention Networks**
https://arxiv.org/abs/1710.10903
paper

[9] **Neural Networks and the Chomsky Hierarchy**
https://arxiv.org/abs/2207.02098
paper

[10] **Neural Networks and the Chomsky Hierarchy**
https://arxiv.org/abs/2207.02098
paper

[11] **On the Measure of Intelligence**
https://arxiv.org/abs/1911.01547

paper

[12] **On the Measure of Intelligence**
https://arxiv.org/abs/1911.01547
paper

[13] **Epistemic Foraging**
https://www.frontiersin.org/journals/computational-neuroscience/articles/10.3389/fncom.2016.00056/full
paper

[14] **Epistemic Foraging**
https://www.frontiersin.org/journals/computational-neuroscience/articles/10.3389/fncom.2016.00056/full
paper