SLUUG Talk: Large Language Models

This repository contains the slides and code for the talk:

- Demystifying Large Language Models (LLMs) on Linux: From Theory to Application

It was given for the St. Louis Unix Users Group (SLUUG) on 2024/2/22 @ 6:30 PM CST.

- SLUUG: https://www.stllinux.org/
- Meetup: https://www.meetup.com/saint-louis-unix-users-group/events/290697932/

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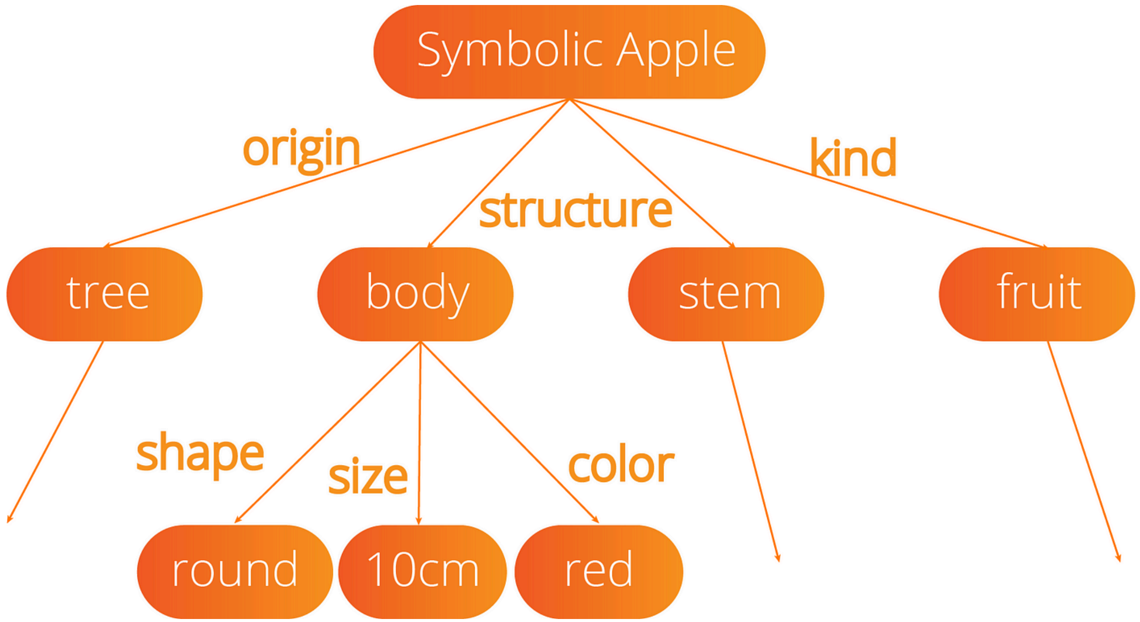
- Important URLs for this talk:
  - Talk link: https://github.com/queelius/sluug-talk-llm 🔗
  - Colab notebook on n-gram model: https://colab.research.google.com/drive/1ak4kOtbIQGXE5kuhhGTd55xu4qRpeZd7?usp=sharing
  - ElasticSearch NLQ demo (down): http://lab.metafunctor.com:6789 (API: http://lab.metafunctor.com:6789/docs)

Outline of Talk

- Theoretical Background
- Go over a simple language model
  - n-gram model (Jupyter Notebook)
  - Easy to understand and helps us understand some aspects of LLMs.
- Show an application of LLMs:
  - Try to make a database search API intelligent (NLP) with small LLMs.
- Open Discussion

Good-Old-Fashioned AI (GOFAI)

- Find a way to symbolically represent the problem and then use logic or rules to solve it.
  - Programming 💻
  - Rule-based systems 🤖
  - First-order logic
- LLMs are *good* at using these tools. 🔨
  - Integrate Prolog with LLM tool-use to help with planning and reasoning?



Reductive Reasoning

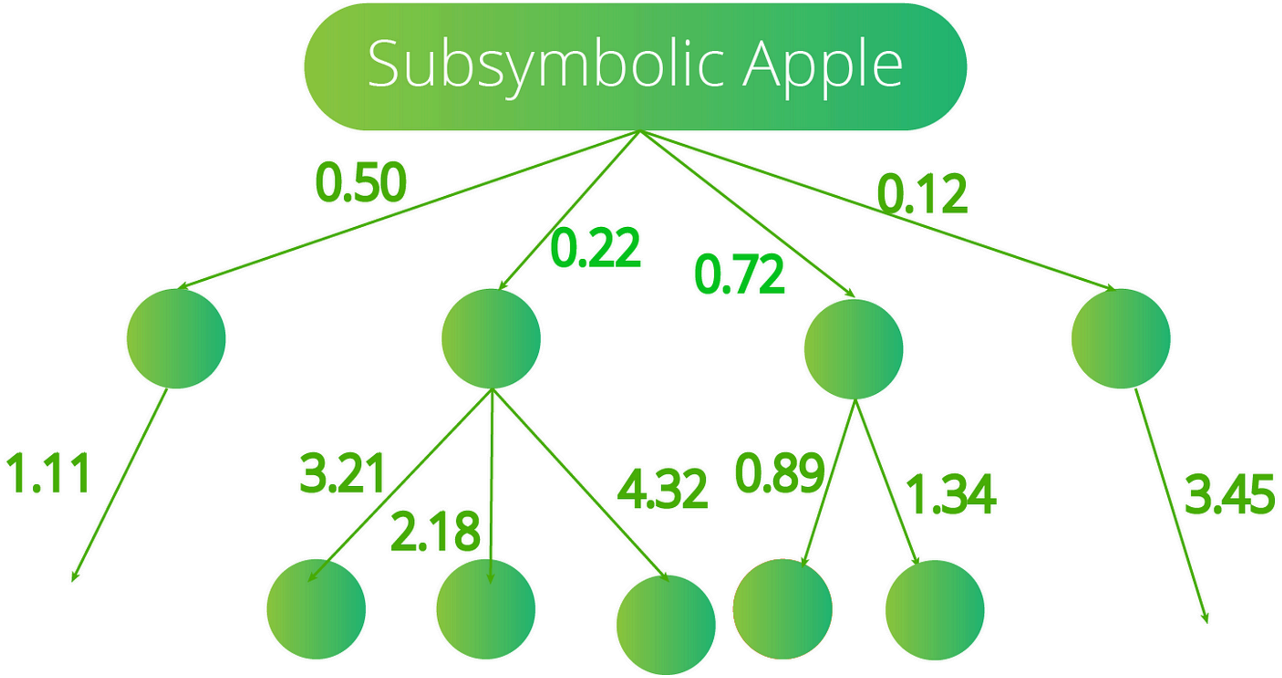
GOFAI works for a lot of problems we care about:

- Filter everything through our small working memory.
  - Inductive bias: Makes assumptions about the world.
  - Help us generalize out-of-distribution. 🧠
- Take big problems and break down into simpler problems.
- Solve simpler problems and combine.

Limits of GOFAI

Many problems are hard to break down into simpler parts.

- Whole greater than the sum of its parts.
- Too complex to solve reductively.
    - We can't program computers to do it. 🤷
    - Identifying cats in pictures? 🐱
    - > The hard problems are easy and the easy problems are hard.
      > -- Steven Pinker
    - Playing with legos is hard but multivariate calculus is easy (for a computer).



How Do Our Brains Work?

Brains programmed by evolution to survive in a complex world.

- It's a prediction engine: it learns to predict the world.
- The unconscious mind is not limited by a small "working memory"
- It can do things we don't understand how to do.
- Brain is a black box. (See: *Interpretable ML*)

Machine Learning

💡 Let's have the computer learn from data.

- Since the real world is too complex, let's have the computer learn from data like we do.
- There are three main types of learning.
  - Supervised Learning (SL)
  - Unsupervised Learning 🔥
  - Reinforcement Learning (RL) 💣
- *Spoiler*: LLMs use self-supervised learning (SSL) and RL (RLHF).

Type of Learning (1): Supervised Learning

Learning from labeled data. We have some input and output data, and we want to learn how to map the input to the output.

- Given an (unknown) function f and a set of input-output pairs $(x, f(x))$, learn a function $\hat{f}$ that approximates f on the input-output pairs.
- E.g., classification: f : [🐱 or 🐶] ↦ { 🐱 , 🐶 }.
    - Use $\hat{f}$ to predict 🐱 or 🐶 for new images.
- Easiest problem to solve in ML. But: limited by data.
- **Fine-Tuning** LLMs is supervised learning: improve it on specific labeled tasks.

Type of Learning (2): Unsupervised Learning

No labeled data. Learn the underlying structure of the data.

- Clustering: Grouping similar data points. (See: *RAG*)
- Dimensionality Reduction: Learn *efficient* representations of the data.
  - Very hard and one of the most important problems in ML.
- Density Estimation: Stochastic estimate of process that generated the observed data. Say the process generates (x, y) pairs and we estimate its density $\Pr(x, y)$.
  - Classification (supervised): $\Pr(y|x) = \Pr(x, y) / \Pr(x)$
- **Pre-training LLMs** is like unsupervised learning. Learn a good representation and probability distribution of the *raw* text using self-supervised learning (SSL).

Final Type of Learning (3): Reinforcement Learning

This is an agentic approach to learning. Agent interacts with environment and learns from the rewards it receives.

- *Goal*: maximize the expected sum of rewards.
- *Spoiler*: Agentic frameworks that include LLMs as a prediction component is a very active area of research.
- `Prediction + Search = Planning`
    - Counterfactual reasoning
- Hypothesis: `Compression = Prediction = Intelligence`
- Big reason a lot of people are excited about Sora.
    - Has everyone seen the Sora videos?
    - "Intuitive" world simulation (embedded in the weights of a giant NN).

Early Failures in ML

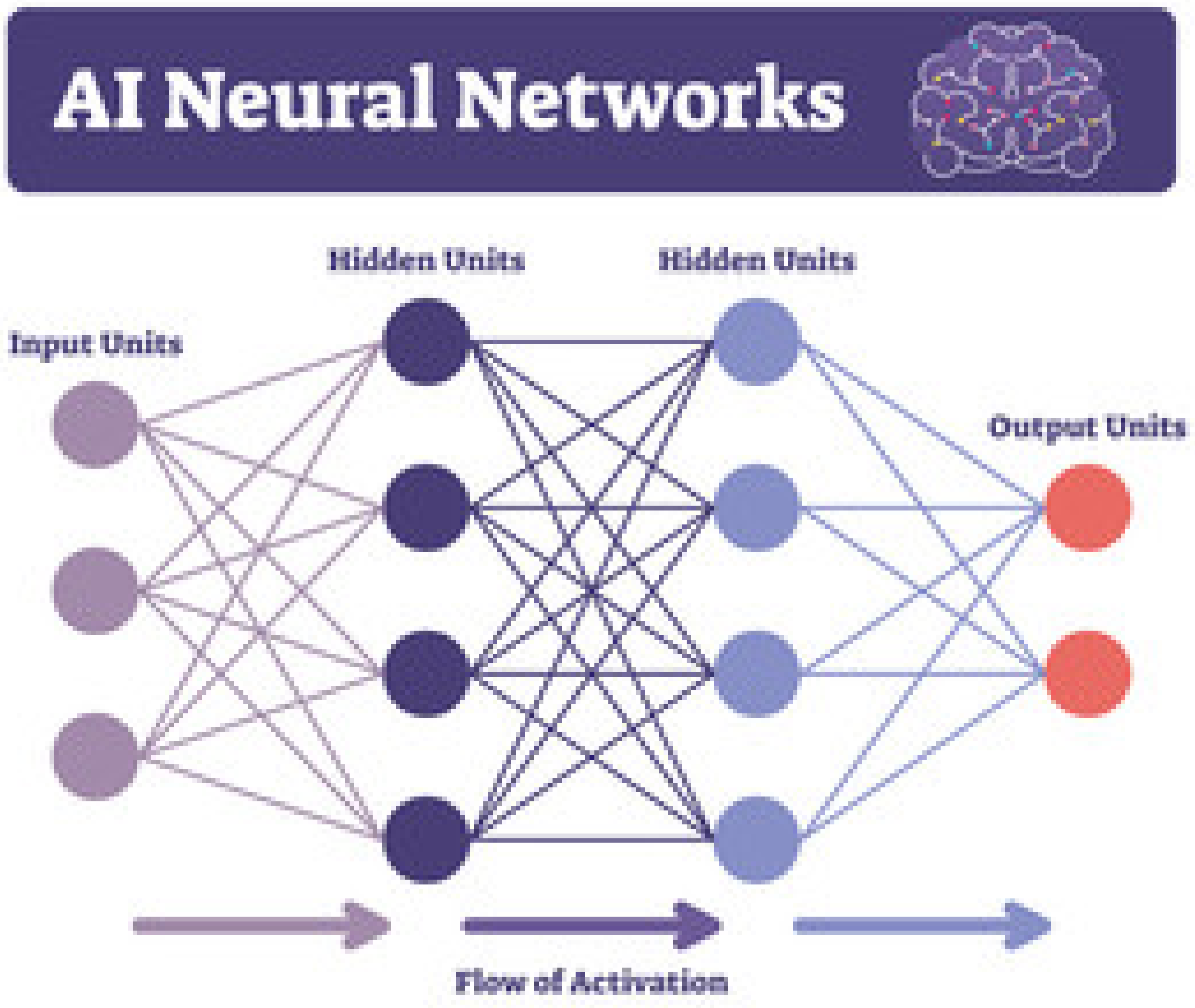
Early efforts in ML were not very successful. Reality is complicated:

$$(x_1, x_2, \ldots, x_n),$$

n extremely large and each x_i some complex object.

- Overfitting, curse of dimensionality, lack of data/compute.
- To combat lack of data/compute, clever solutions developed.
- Many of these methods are no longer around.

  > "The biggest lesson that can be read from 70 years of AI research is that general methods that leverage computation are ultimately the most effective, and by a large margin."
  > -- Richard Sutton's Bitter Lesson



Neural Networks

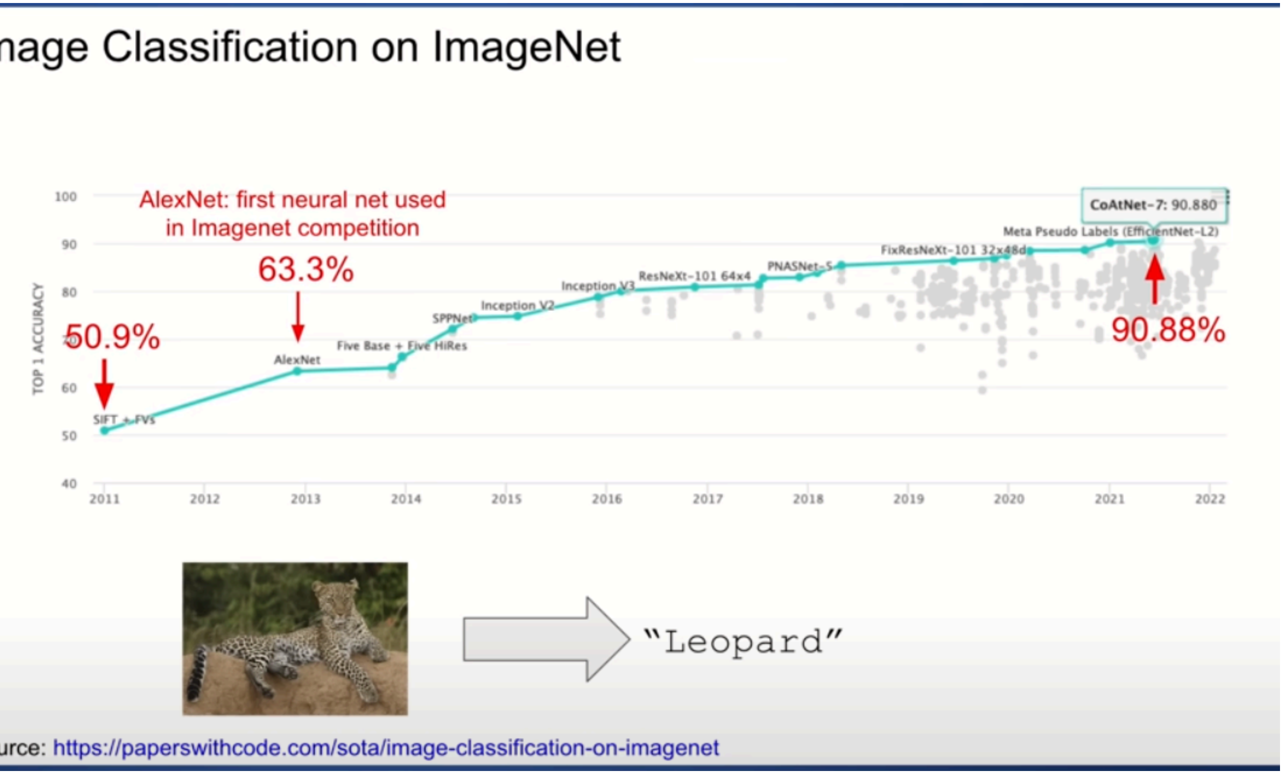
Neural Networks (NN) are one the solutions that stuck around.

- It fell out of favor for a while, but it's back.
- Universal function approximator.
  - Can learn to represent any function.
  - But: need a lot of data to do so and be difficult to train.
- NNs seem to scale to as much data and compute as we can throw at them.

Inductive Bias

Observations may have an infinite set of hypothesis that are compatible with the data.

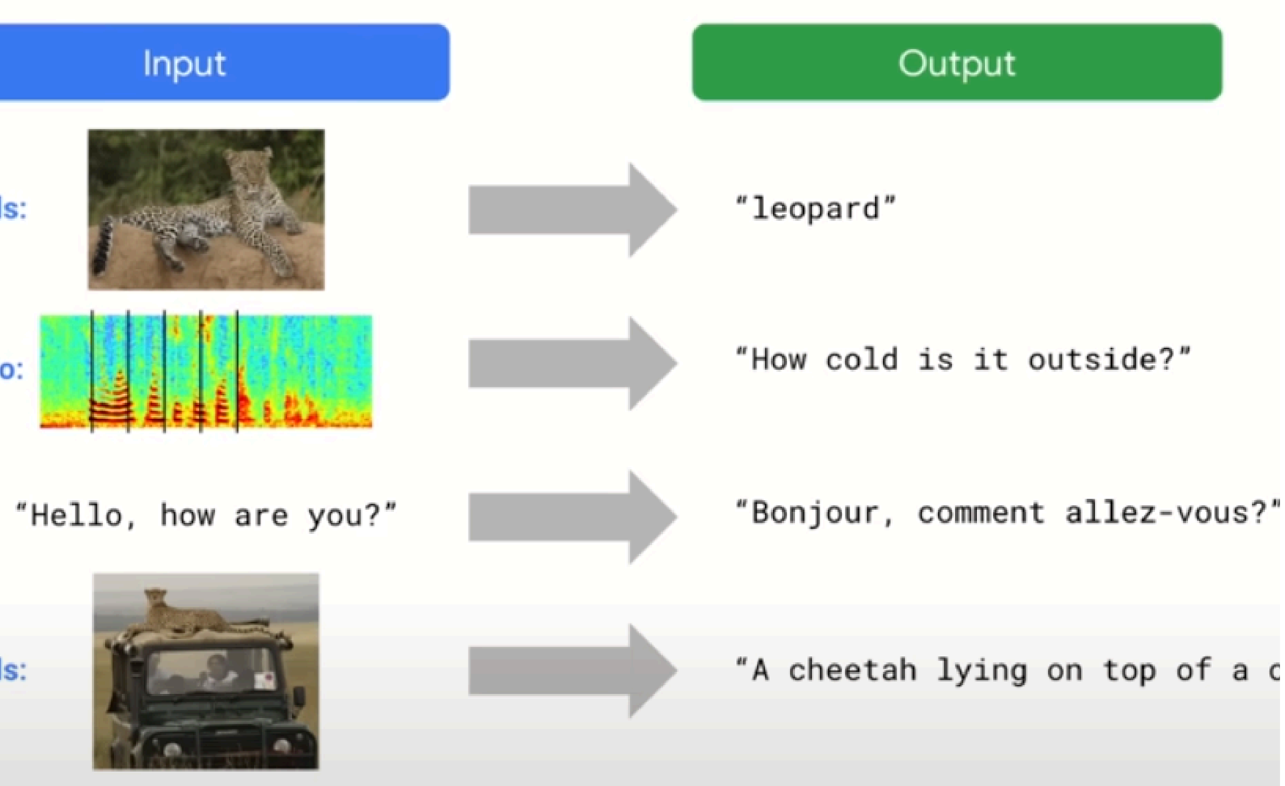
- **Inductive Bias**: The set of assumptions that the model makes about the data.
- **Occam's Razor**: choose the simplest hypothesis that is compatible with the data. (See *Solomonoff Induction*.)
- Generalizing out-of-distribution (OOD) from inputs not in the training data.
- **Problem**: We are almost *always* out-of-distribution.
    - Except in toy problems (see: early successes)
- Good inductive biases are necessary for generalization.
- **No Free Lunch Theorem**: No model is optimal for all tasks.



Era of Deep Learning

One of the hardest parts is learning sample efficient representation of the data.

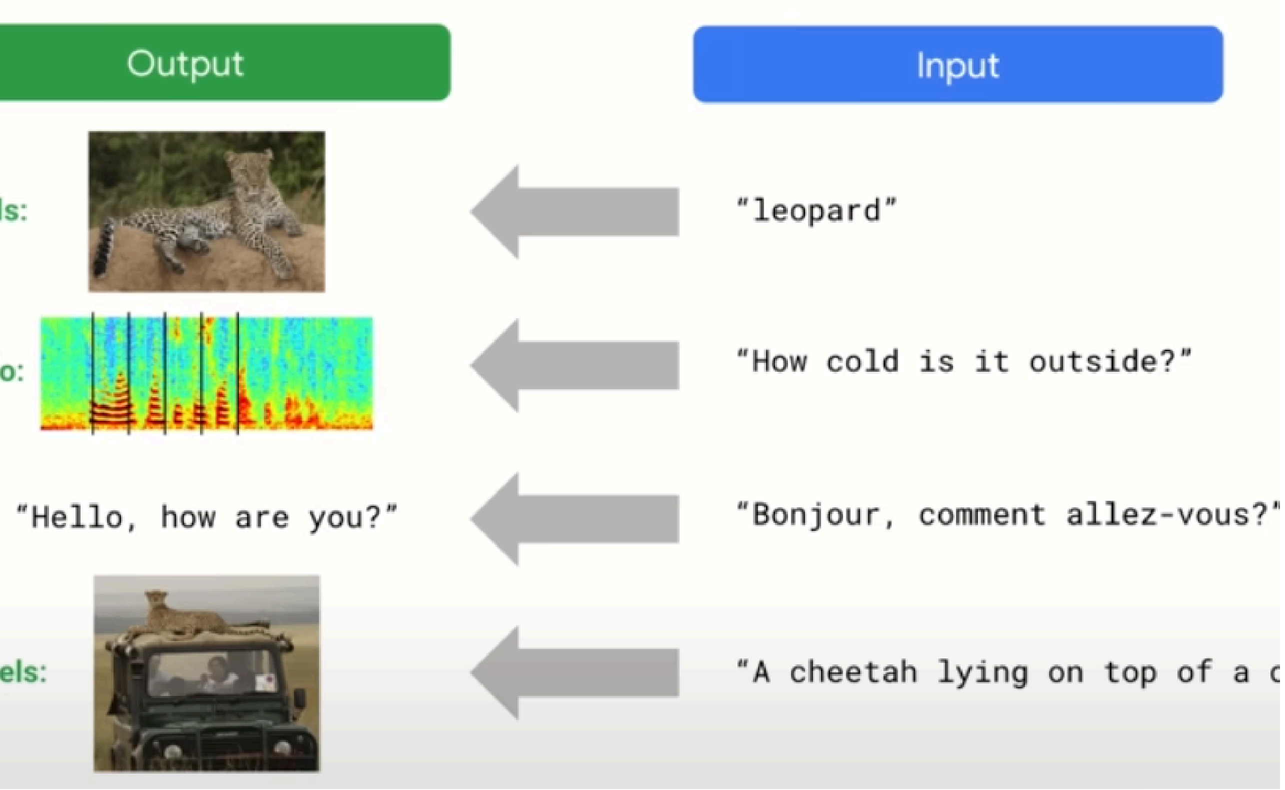
- Layers of NN learn progressively higher-level representations: `Pixels -> Edges -> Objects`
- AlexNet (2012) was the first to show that deep learning could work well on large-scale datasets.



Era of Deep Learning (cont.)

DNNs (feed-forward) learn little circuit programs that can generate parts of the training data. (Image stolen from Jeff Dean's slides.)

- Hundreds of layers: can learn pretty complicated programs.
- (What a human can do in a half a second, a DNN can do?)



Era of Generative AI

Generative AI "reverses" the arrows - Image to text, image to image, etc.

- They learn something about the data generating process (DGP).
- They have completely changed our expectations of what computers can do.

Era of Generative AI (cont.)

We now have computers that can see, hear, understand, and generate all of these things.

Let's go look at **Sora**: generative video, or world(s) simulator?

- **Scaling**: And increasing the scale (data, compute) increase their capabilities. See: Scaling laws.
    - Need a lot more *compute*.
    - It's going to get wild(er).
    - Hypothesis: `Prediction = Compression = Intelligence`.

Large Language Models (LLMs)

Autoregressive (AR) models learn a probability distribution over training data by using self-supervised learning (SSL):

$$\Pr(x_1, x_2, \ldots, x_T) = \prod_{t=1}^{T} \Pr(x_t | x_1, \ldots, x_{t-1})$$

- This is hard to learn, but with enough data and compute, a lot seems possible.
- LLMs have a nice advantage since language is designed to have a very low dimensionality and have a high signal to noise ratio.
  - Representation learning is easier in language than in other domains.
    - Still learns representations (`word2vec`)
- **Language** represents much of the things that humans care and think about, so learning to predict it is a kind of general intelligence. (See: Sparks of AGI by Microsoft)

Sampling from LLMs

There are many different ways to sample from LLMs and change the behavior of the model.

- **Temperature**: Rescaling the logits before applying the softmax function.
    - $T = 1$: estimates the probability distribution.
    - $T < 1$: reduces randomness, i.e., more predictable outputs.
    - $T > 1$: increases randomness, i.e., more unpredictable outputs.

Good for controlling *exploitation* vs *exploration* if repeatedly sampling from the model to generate new or different outputs.

- **Top-k and Top-p Sampling**: Choose the top-k or top-p tokens and sample from them.
- **Beam Search**: Explore multiple paths and sample based on that joint probability.

Prompting Strategies

Early models were very sensitive to the prompt.

- Makes sense, they were trained to generate the data.
- If you condition on crazy data, you get crazy outputs.

$$\Pr(\text{more crazy}|\text{crazy})$$

Various prompting strategies have been developed to help the model generate more reliable outputs:

- Chain-of-thought (CoT)
- Tree-of-thought (ToT)
- and so on...

LLM Overview

Basic idea: train a model to predict the next token in a sequence of tokens.

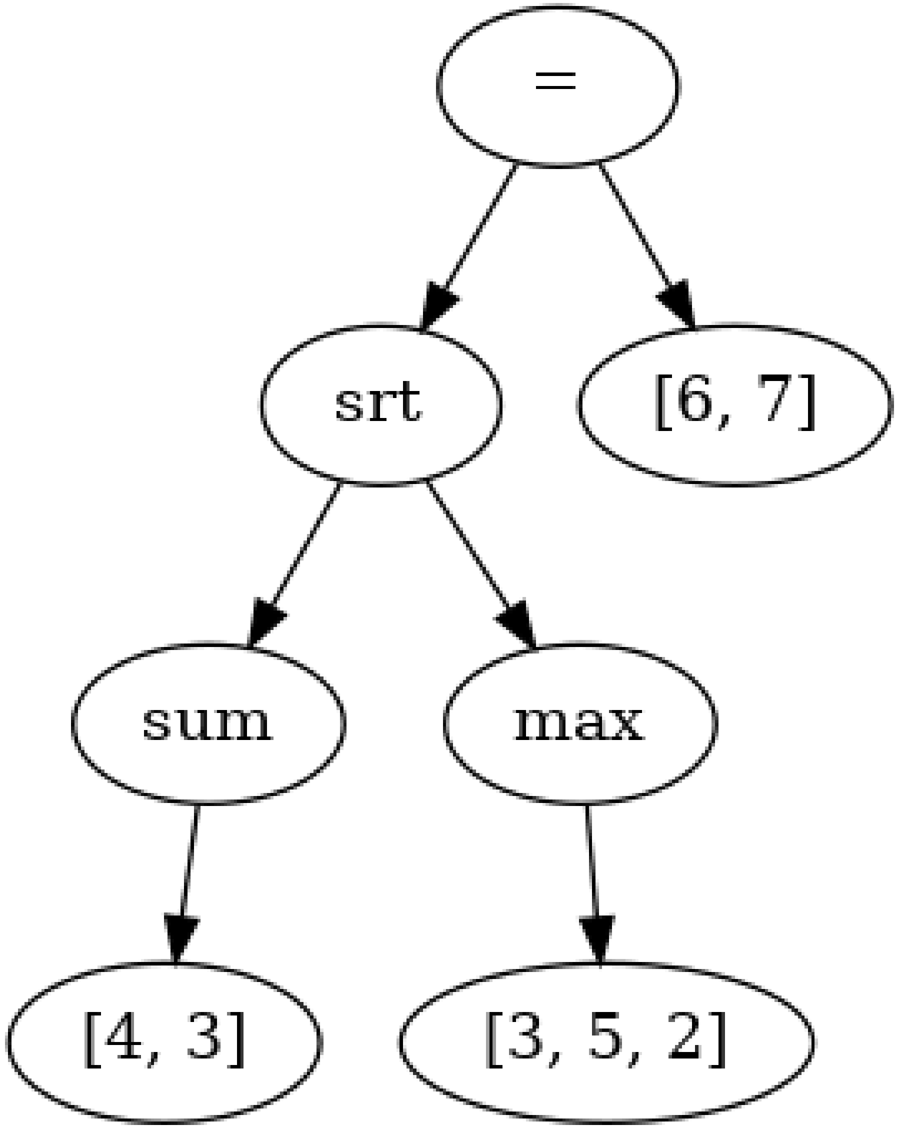
- **Task**: Given a sequence of tokens, predict the next token.
    - Pre-Train model to learn raw data distribution using SSL.
    - Fine-tune model to a specific dataset that is more relevant to a task.
    - RLHF model to bias it to produce outputs that people prefer.
- **Goal**: Enable the generation of new data points for a given task.

OOD Generalization

At inference, outputs are almost always out-of-distribution (OOD).

- *In-Context Learning*: Transformers seem to be pretty good at generalizing from data that was not seen during training.
- Learning to predict the next token when the data is sufficiently complicated may require a general kind of intelligence.
- *Causal inductive bias*: The model is biased to predict the next token based on the evidence of the previous tokens.

Example: "Based on all the previous evidence, I conclude that the murderer is ___". To do this well, it seems you must be able to reason about the evidence.



Naive N-Gram Model (AR) Over Bytes

We consider an AR-LM over bytes (256 tokens):

- *Algorithmic training data*: Partial expression trees.
  - *Sparse* markov chain of order $O(256^n)$ states.
- Analyze how well model predicts the next token given the context.
- How well does model capture the underlying process?
  - *Spoiler*: It doesn't do well.

Implementation Notes

- We represent our n-gram model as a dictionary of dictionaries:
    - Outer dictionary is indexed by context.
    - Inner dictionary is indexed by next token.
    - Each `token | context` maps frequency in training data.
- This is simple model and simple data
    - Hopefully, exploring its properties can help us understand LLMs.

Colab

Let's go to the notebook.

- If you want to follow along, Colab is available at: https://colab.research.google.com/drive/1ak4kOtbIQGXE5kuhhGTd55xu4qRpeZd7?usp=sharing 🔗
- See my GitHub: https://github.com/queelius/sluug-talk-llm 🔗

Colab Comments

Inductive Bias: Throwing away oldest bytes is a strong inductive bias:

- Not necessarily true that the next byte is less dependent on the oldest bytes.

Generative Model: generate text by starting with a any context and then sampling from the probability distribution for that context to get the next token.

- Repeat until we have generated the desired number of tokens.
- Same way LLMs work (but they work well).

Colab: Advantages of Our Model

Our model has some advantages compared to AR-LLMs. Since we simply *store* the data:

- Easy to implement.
- Easy to make it a lifelong learner. Store *more data*.

Colab: Disadvantages of Our Model

But, compared to more sophisticated models, they have huge disadvantages:

- n-gram model is not able to capture long-range dependencies in the data.
    - Number of states grows exponentially with the order of the model.
    - It cannot scale to large contexts, and therefore cannot understand nuances in the data.
- n-gram model does not generalize out-of-distribution very well.
    - Since language is a high-dimensional space, *most* contexts have never been seen before.

Colab: Conclusion

Key concept in ML: A *good* model *compresses* the data.

- There is a notion that *compression* is a proxy for *understanding*.
- Take a *physics simulation*: we don't need to store the position and velocity of every particle.
    - We can just store the starting conditions and then let the laws of physics play out.
    - Not perfect, but perfect prediction impossible.
        - Only need to predict it well enough to make informed decisions.
- `Prediction = compression = intelligence`
    - The brain may be a good example of this.

Finite State Machines

We can view AR-LMs as finite state machines (if deterministic) otherwise Markov chains without loss of generality.

- Computers are FSMs, just very large ones.
- LLMs are also very large FSMs.

https://www.lesswrong.com/posts/7qSHKYRnqyrumEfbt

- Thus, AR-LLMs are differentiable computers that can learn from examples.

Tool-Use

There is a lot of training data about how to use tools and APIs. 🔨

- Large LLMs like GPT-4 do a good job predicting when and how they should use tools.
- Let's go over to the ElasticSearch NLQ demo. 🔦

ElasticSearch Demo

- Making all endpoints on the internet and UIs intelligent with small and fast LLMs.
- As a trial, we are using ElasticSearch as a backend to enable natural language queries (NLQs) on ElasticSearch indexes (databases).
- Key take-aways: GPT-4 / GPT-3.5 are good, small LLMs not quite there yet.
    - We have some ways to possibly improve them though. More on that later.
    - And, of course, today's large models are tomorrow's small models.
        - Desperately need more compute!

ElasticSearch: What Is It?

- An open source, scalable search engine.
- Supports complex queries, aggregations, and full-text search.
- Can be difficult to use.
- Suppose we have `articles` index with `author` and `title` fields and want to count the number of articles by author:

```
{
  "size": 0,
  "aggs": {
    "articles_by_author": {
      "terms": { "field": "author" }
    }
  }
}
```

FastAPI: What Is It and How Do We Use It?

- A fast web framework for building APIs with Python.
- We are trying two things:
  - Using ElasticSearch backend for storage and search.
  - Using LLMs to convert natural language queries (NLQ) to ElasticSearch queries.
- We expose a single endpoint `/{index}/nlq` that takes an index and an NLQ and returns a result from ElasticSearch.
  - Hopefully the result is useful!
- Later, remind me to open my firewall to allow access.

Structure of Indexes

I populated ElasticSearch with a two example indexes:

- `articles`: A simple index with `author`, `title`, and 'publication_date' fields.
- `gutenberg`: A more complex index with `author`, `publication_date`, `title`, and `content` fields.

Code

Let's look at some code. We'll switch to the code editor. There are a few files we need to look at:

- `main.py`: The FastAPI app. We can probe it using the Swagger UI at `http://lab.metafunctor.com:6789/docs`.
- There is a crude frontend at `http://lab.metafunctor.com:6789/`.
  - I made the frontend by chatting with ChatGPT-4. By chatting, I mean asked two ill-formed questions and copied its code blocks.
  - See this link: https://chat.openai.com/share/9c95ba2e-94e7-4d9f-ae89-095357fc39bd
- `nlq.py`: The module that handles the NLQ to ElasticSearch query conversion.
- `examples.py`: A crude example database. We'll talk about this in a bit.

Issues

- GPT-4 is good at converting NLQs to ElasticSearch queries, but it's slow and expensive to use at scale.
  - We only need to use an LLM for a relatively narrow task.
  - Maybe we don't need the full power of GPT-4?
- Small LLMs, like `llama2`, did poorly on converting NLQs to ElasticSearch queries.

Idea #1: Use GPT-4 to "Teach" Smaller Models

Use GPT-4 to generate high-quality examples for smaller LLMs.

- Feed examples into the context of the small LLM to do In-Context Learning (ICL).
  - **ICL**: a model can generalize to new NLQs
- How? Every now and then, use GPT-4 to do the task and store its NLQ to ElasticSearch query in example database.
- Let's look at the `examples.py` code.
  - DB is just a Python `{}` that doesn't persist.
  - Didn't have the time to use a proper database.
    - Ironic considering this is all about how to use ElasticSearch!

Issues

The smaller models, like `llama2:13b` , do not seem to generalize from the examples very well.

- They often do better without "polluting" their context with too much information.
- More tweaking? Or are these small models simply not up to the task.

Idea #2: RAG (Retrieval-Augmented Generation)

Maybe the smaller models need to be fed with more *relevant* examples. Use RAG to find relevant examples for the given index and NLQ 💡

- Send the context through a language model to get a dense representation.
- Store the representation of the examples in the database.
- Find examples closest to the context of the NLQ and sample from them.
- Insert the high-quality examples into the context of the small LLM to do ICL.

Idea #3: Fine-Tuning

- Fine-tune the smaller models on far more high-quality examples.
- Small LLMs won't have to In-Context Learn as much.
- See my GitHub repo: https://github.com/queelius/elasticsearch-lm
    - Its README has a lot of verbiage.
    - I just ran it through GPT-4 and didn't bother to edit it much.

Discussion