Today I'll be talking about translating natural language into executable programs.
**TASK**: parse multi-step instructions into programs

Let's imagine that you're working in a chemistry lab, and you have a robot assistant. You'd like to say things like "pour the last green beaker into beaker two", etc.

The robot then needs to translate each of these instructions into an executable program.

To train this robot, it is very time consuming to label each command with the right program, or the user may not even know how to write code. In contrast, it's quite easy to move the beakers yourself and demonstrate what should happen.

So, we consider a learning setup where the robot sees a demonstration, but does not actually observe the correct program.

This is really a classic "weak supervision", or "learning from denotation" task, which has had a rich history in the semantic parsing literature.
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For this talk, I'll be highlighting one big problem with weak supervision, and how we solve it.

In particular, researchers have noted that weakly supervised models tend to learn spurious programs, and what we call "superstitious behavior".

So, what I do mean by that?
**PROBLEM:** spurious programs and superstitious behavior

At training time, this is what our model sees.

We give it an input, consisting of an utterance and a start_state.

It then has to find a program which produces the output goal_state.

The problem is that there are multiple ways to get from input to output.
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The problem is that there are multiple ways to get from input to output.
PROBLEM: spurious programs and superstitious behavior

input

utterance = "pour the last green beaker into beaker two"

start_state =

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```

pour(hasColor(green)[-1], beaker[2])

output

goal_state =

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```

For example, here is the correct program, which accurately reflects the utterance.
**PROBLEM:** spurious programs and superstitious behavior

**input**

- **utterance** = "pour the last green beaker into beaker two"
- **start_state** = [Image of beakers with colors and liquid levels]

**pour(hasColor(green)[-1], beaker[2])**

*last green beaker*

**output**

- **goal_state** = [Image of beakers with colors and liquid levels]

For example, here is the correct program, which accurately reflects the utterance.
**PROBLEM:** spurious programs and superstitious behavior

**Input**
- **Utterance:** "pour the last green beaker into beaker two"
- **Start State:**

**Program:**
```
pour(hasColor(green)[-1], beaker[2])
```

- **Last Green Beaker**
- **Beaker Two**

**Output**
- **Goal State:**

For example, here is the correct program, which accurately reflects the utterance.
**PROBLEM**: spurious programs and superstitious behavior

- **Input**
  - `utterance` = "pour the last green beaker into beaker two"
  - `start_state` = ![initial_state_image]

- **Output**
  - `goal_state` = ![goal_state_image]

- `empty(beaker[3]); add(hasColor(red), green)`

But this program also gets us to the goal state.

If I switched to a different chemistry table and gave the same command, I would not want to run this program.

Ironically, this problem gets worse as your programming language becomes more powerful.
A more expressive language means there are more wrong ways to get to the goal_state.
**PROBLEM**: spurious programs and superstitious behavior

**input**

*utterance* = "pour the last green beaker into beaker two"

**start_state** =

```
empty(beaker[3]); add(hasColor(red), green)
```

**goal_state** =

```
empty 3rd beaker
```

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**PROBLEM:** spurious programs and superstitious behavior

\[
\begin{align*}
\text{input} & \quad \text{utterance} = \text{"pour the last green beaker into beaker two"} \\
\text{start state} & = \text{empty(beaker[3]); add(hasColor(red), green)} \\
\text{output} & \quad \text{goal state} = \text{empty 3rd beaker the beaker with red liquid}
\end{align*}
\]

But this program also gets us to the goal state.

If I switched to a different chemistry table and gave the same command, I would not want to run this program.

Ironically, this problem gets worse as your programming language becomes more powerful. A more expressive language means there are more wrong ways to get to the goal state.
So, this is really a problem you might encounter any time you are working with weak supervision.

In fact, humans certainly aren’t immune to this either.

At some point, we’ve all studied hard for an exam. Maybe we did well on that exam, from which we rightly concluded that studying helps.

But maybe we were also wearing purple socks that day. And now we think, "hmm, my purple socks are lucky".
So, this is really a problem you might encounter any time you are working with weak supervision.

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So, enough about humans. Let's now look at how learning algorithms get confused.
We'll look at two common approaches to the weak supervision problem.
Starting with reinforcement learning.
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The first thing we need to do is convert program generation into a sequential decision making problem.

By reformatting the code in postfix notation, we can represent the program as a sequence of tokens.

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By reformatting the code in postfix notation, we can represent the program as a sequence of tokens.

And now the task is simply to sequentially generate tokens from left to right.
If we organize all possible program sequences in a prefix trie, we get this picture.

From the RL point of view, each node in the tree is a state, and the arrows are actions which transition you to new states.

When you hit a leaf node, the episode terminates.
And the path that you took uniquely defines a complete program.

Given this utterance, the right response is to take the path highlighted in yellow.
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Reinforcement learning

\[ x = "Mix the last yellow beaker" \]

Notation-wise, we'll call the utterance \( x \), and we'll call each program \( z \).
Once the agent generates a program, we then execute the program and give it reward 1 if the output is right, 0 otherwise.

The agent itself has a stochastic policy, meaning that there is some randomness in the actions it takes.

We then train the agent to maximize its expected reward.
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Reinforcement learning

\[ x = \text{"Mix the last yellow beaker"} \]

RL agent generates program

\[ z \]

execute program

\[ y = \text{[Image of a beaker partially filled with liquid]} \]

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Reinforcement learning

\[ x = "Mix the last yellow beaker" \]

\[ R(z) = 1 \text{ if } y \text{ is correct} \]
\[ 0 \text{ otherwise} \]

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In the marginal likelihood view, we put on our statistics hat and imagine a generative model of our data. First, there is some conditional distribution over programs, given the utterance. Then, there is some conditional distribution over outcomes, given the program.

We then want to maximize the overall likelihood of this generative model. And it's marginal likelihood, because we have to marginalize out over the latent program, z.
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And it’s marginal likelihood, because we have to marginalize out over the latent program, z
Those two descriptions actually sounded pretty similar
Comparing RL and MML

**RL**

\[
E_z [R(z)] = \sum_{z \in Z} R(z) p_\theta(z | x)
\]

**MML**

\[
p(y | x) = \sum_{z \in Z} p(y | z) p_\theta(z | x)
\]

\[
y = \text{goal\_state} \quad z = \text{program} \quad x = \text{utterance}
\]

And in fact, if you write out both objectives, we see that they’re almost the same.
The only difference is right here.
But now let’s think about \(p(y | z)\). It’s the distribution over outcomes, given the program.
Since programs execute deterministically, this term is always 0 or 1, and is in fact identical to \(R(z)\).
And in fact, if you write out both objectives, we see that they're almost the same.
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**RL**

$$E_z[R(z)] = \sum_{z \in Z} R(z) p_\theta(z \mid x)$$

**MML**

$$p(y \mid x) = \sum_{z \in Z} p(y \mid z) p_\theta(z \mid x)$$

$y = \text{goal\_state}$  
$z = \text{program}$  
$x = \text{utterance}$
So you might now think that RL and MML are the same.

But they are only the same when thinking about a single training example. Let’s look at their objectives for multiple examples.

In RL, we maximize the average reward over examples.
In MML, we maximize the total log likelihood.

It turns out that the MML objective has an extra log. In a few slides, we’ll see why that’s important.
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$y = \text{goal\_state}$ \hspace{1cm} $z = \text{program}$ \hspace{1cm} $x = \text{utterance}$

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Why do we get spurious programs in RL and MML?
This is the last math slide you will see in this talk, but it contains the main idea, so I'll try to break this equation down.

First of all, the gradient involves a sum over all programs. Since there are millions of possible programs, this sum is approximated in practice.

Each term is weighted by the reward. Since most programs get zero reward, a lot of terms in this sum disappear.

For the remaining programs which do get reward, we take a gradient step to increase their log probability. Finally, we weight the gradient by how much we already like the program.

The MML gradient is actually just the RL gradient, but rescaled by the expected reward, so it's almost the same.

We will argue that this term is really the main culprit responsible for spurious programs.
Gradients for RL and MML

\[ g^{RL} = \sum_{z} p_{\theta}(z \mid x) R(z) \nabla_{\theta} \log p_{\theta}(z \mid x) \]

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$$g^{RL} = \sum_z p_\theta(z \mid x) R(z) \nabla_\theta \log p_\theta(z \mid x)$$

*gradient weight*

To make that argument, we’ll focus on this quantity, which we call the gradient weight.
Suppose we have a model which places fairly low probability on all programs to begin with.

But we find out that two of them get reward.
The rich get richer, the poor stay poor

\[ g^{\text{RL}} = \sum_z p_\theta(z \mid x) R(z) \nabla_\theta \log p_\theta(z \mid x) \]

Suppose we have a model which places fairly low probability on all programs to begin with.

But we find out that two of them get reward.
In our gradient step, we upweight them. The red bars show the size of the gradient weight.
The rich get richer, the poor stay poor

$$g^{RL} = \sum_{z} p_{\theta}(z \mid x) R(z) \nabla_{\theta} \log p_{\theta}(z \mid x)$$
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\[
g^{\text{RL}} = \sum_z p_\theta(z \mid x) R(z) \nabla_\theta \log p_\theta(z \mid x)
\]

We then repeat the gradient step a few times.
The rich get richer, the poor stay poor

\[ g_{RL} = \sum_z p_{\theta}(z \mid x) R(z) \nabla_{\theta} \log p_{\theta}(z \mid x) \]
After a while, $z_4$ dominates $z_1$ by a lot, just because it had a head start.
The rich get richer, the poor stay poor

\[ g^{\text{RL}} = \sum_z \psi_\theta(z \mid x) R(z) \nabla_\theta \log p_\theta(z \mid x) \]

And if \( z_4 \) were spurious, we would be in trouble
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\[ g^{RL} = \sum_z p_\theta(z | x) R(z) \nabla_\theta \log p_\theta(z | x) \]

And if \( z_4 \) were spurious, we would be in trouble.
So let's rewind and think about what we could have done instead.
Intuitively, we’d just like to give both programs the same boost.
SOLUTION

combining the best of RL and MML

1. *meritocratic gradient weights*
2. randomized beam search

And we can do exactly that, which brings us to our first solution
What we do is take the initial gradient weights and renormalize them so that they sum to 1.

Then we think of the gradient weight as a probability distribution, and raise the temperature of that distribution. If you raise the temperature to infinity, you end up with equal weights.

Interestingly, the weights on the left correspond to the original RL gradient while the renormalized weights correspond exactly to the MML gradient.

We go one step further and adjust the temperature of that distribution, yielding what we call a meritocratic gradient.
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We go one step further and adjust the temperature of that distribution, yielding what we call a meritocratic gradient.
When we compare the impact of using these different gradient weights, we see some pretty interesting results.

Across different tasks, the meritocratic update is always better or as good as the MML update.

The red bars for RL are actually all near zero. We found that when you try to do the exact RL update, things really don’t train that well, and a significant amount of epsilon greedy dithering was needed to actually make it work.
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Another benefit we noticed was that more meritocracy leads to faster overall training speed. Note that when temperature = 1, this is identical to MML.
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So, that closes our discussion of the gradient weight.

But one thing I didn’t explain is how we handle the intractable sum over millions of programs.
This brings us to our second contribution, randomized beam search.
The standard approach in RL for approximating the intractable sum is to use sampling.

Rather than enumerating all programs, we just sample one program from the model policy, and perform the update.

The initial policy is quite bad, so at first, it is just randomly exploring.
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The initial policy is quite bad, so at first, it is just randomly exploring.
Once REINFORCE finds a program that earns reward, it upweights all actions along that path.
But if you upweight that path, then you are more likely to go there next time and upweight again, and this one path eventually steals all the probability from the alternatives.

At this point, there is very low probability that REINFORCE will ever discover the correct program.

This is a problem for meritocratic updates because we cannot renormalize over multiple programs if we only find one program.
Our solution is to borrow a standard idea from the MML literature, where beam search is very common.
In beam search, rather than taking one path, we try to take multiple paths simultaneously.

Here, even though one path has much higher probability, we will take all three, because we have a beam size of 3.
Beam search (beam_size = 3)
Beam search (beam_size = 3)

then we look at our next options, and again take the top 3
Beam search (beam_size = 3)
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and so on
Beam search (beam_size = 3)

and so forth
Now that we have multiple programs, we can normalize over them and do our meritocratic update
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Beam search (beam_size = 3)

REINFORCE sampling

Also, compared to REINFORCE, this guarantees coverage of at least 3 programs, even if the model has concentrated its probability on one.
On the other hand, typical implementations of REINFORCE usually get a big boost in performance from being epsilon greedy. That is, epsilon of the time, they ignore the policy and choose a random action.
Randomized beam search

So we decided to add this trick to beam search.
Randomized beam search

At each time step, we randomly replace a few elements on the beam with random choices.
Randomized beam search
Randomized beam search
Randomized beam search
Purple nodes indicate where we chose randomly.
Randomized beam search

Extensions: diverse beam search

This is a very basic way of adding diversity to beam search, and you could certainly extend this to more sophisticated approaches.
But interestingly, we found that this very simple trick really boosts the performance beam search.

Across all domains, we see that randomized beam search performs much better than its classic counterpart.

In fact, we found that just randomizing the beam is actually better than increasing the beam size by 4x. So, it’s interesting to note that this trick isn’t more commonly used.
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Overall results on SCONE

And the result is that we do consistently better across all of the tasks in SCONE.

The MML results come from previous work, which used a log-linear model with manually crafted features. The REINFORCE and RandoMer use the exact same neural architecture, but are just trained differently.
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So, to wrap things up:

In this talk we presented the task of parsing language into programs

We introduced this idea of spurious programs and superstitious behavior, which is quite common in weak supervision

And, as far as I can tell, we are the first to really propose a solution to this problem, in the form of more balanced exploration and gradients
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Conclusion

**TASK:** translate language into programs, learning from weak supervision.

**PROBLEM:** spurious programs and superstitious behavior.

**SOLUTION:**
combine RL + MML = RandoMer to combat spurious programs

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  - Rich literature on **reinforcement learning** (REINFORCE, actor-critic, etc.)
  - Rich literature on learning **latent variable models** (EM, method of moments, variational inference)
  - Many more interesting connections to explore