IN5550: Neural Methods in Natural Language Processing
Sub-lecture 3.4
Computation graphs

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Contents

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- The good news is that we can use reverse-mode automatic differentiation (i.e. back-propagation) to automatically calculate the gradients
- This means that instead of spending lots of your time deriving gradients by hand, you can use all that time to explore model options.

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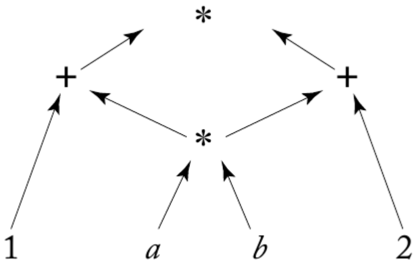

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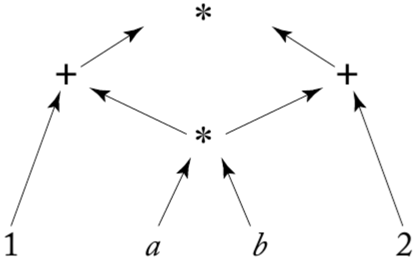

directed acyclic graph (DAG)

Question: **what does this graph produce when $a = 2, b = 1$?**

Computation graphs

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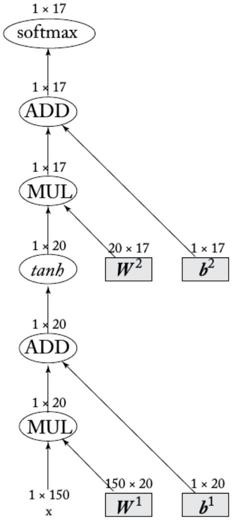
- Operations, parameters and variables are nodes in a DAG.
- The whole graph should be differentiable.

Computation graphs



Think over before the Q&A session / lab session:

- How many total layers are there in this computation graph?

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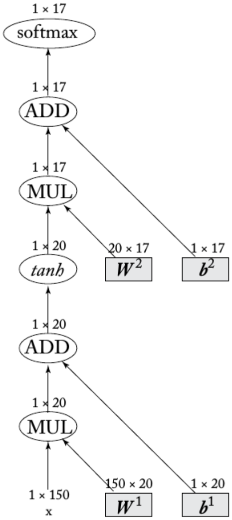

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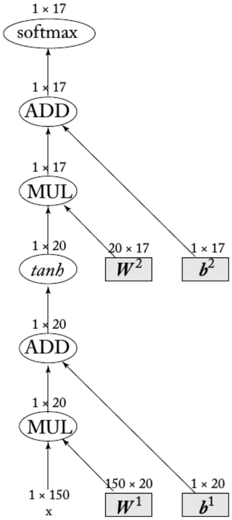

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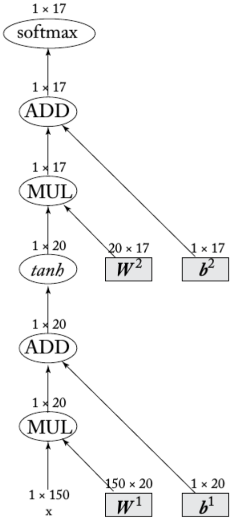

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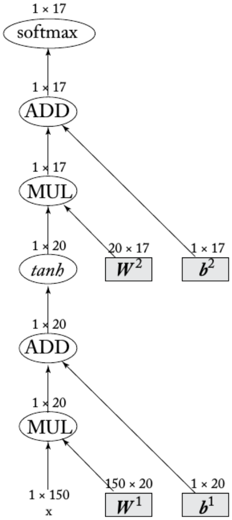

Think over before the Q&A session / lab session:

- How many total layers are there in this computation graph?
- How many hidden layers?
- What is the shape of its output?
- **How can you describe what this architecture does?**
- Any NLP task for which it can be used?

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Loss calculation

- Loss functions are as a rule the same as with linear models;
- cross-entropy is arguably the dominant one: $L(\hat{y}, y) = -y \ log(\hat{y}) - (1 - y) log(1 - \hat{y})$
- NB: the output should be squashed by sigmoid or like.

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- NB: the output should be squashed by sigmoid or like.
- ...however, new loss functions are also being introduced:
  - e.g., Von Mises-Fisher loss [Kumar and Tsvetkov, 2018], etc.

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- Gradient is computed using a special algorithm:
- **back-propagation a.k.a reverse differentiation** [Rumelhart et al., 1986];
- propagating loss values backwards through all layers...
- ...religiously computing derivatives at each.

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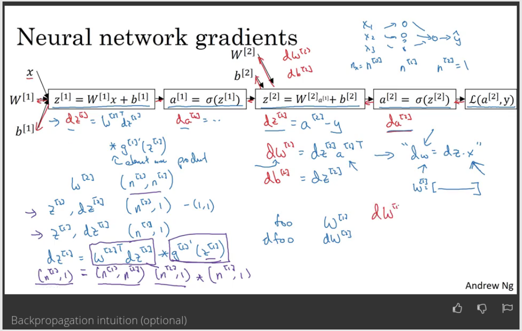

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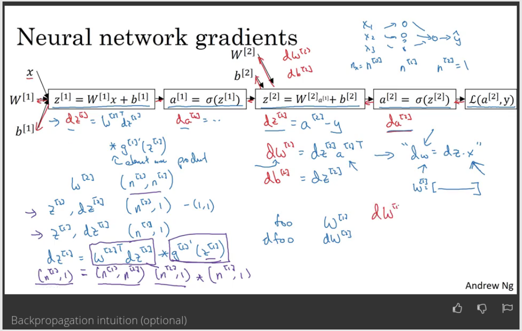

- ... fortunately, automatic tools for gradient computation with *backprop* do exist and are well-developed!

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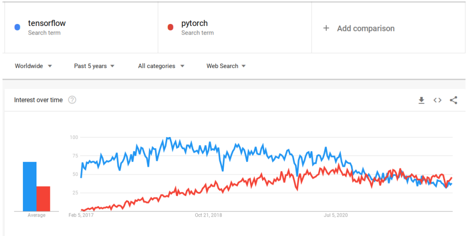
Every tech giant wants to introduce its own 'definitive deep learning library'. The field is very competitive.



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- Makes it easy to use deep learning elements in your code.
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- Stay tuned!

References I

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