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

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Computation graphs



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Computation graphs



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Computation graphs



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Computation graphs



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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.

Computation graphs



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- computation is broken down into separate operations;

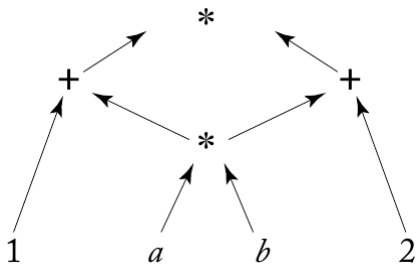
Computation graphs



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Computation graphs

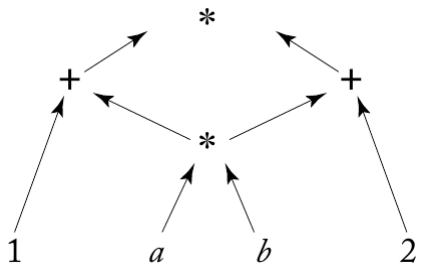
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Question: **what does this graph produce when** $a = 2, b = 1$**?**

Computation graphs



Training basics

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- Operations, parameters and variables are nodes in a DAG.

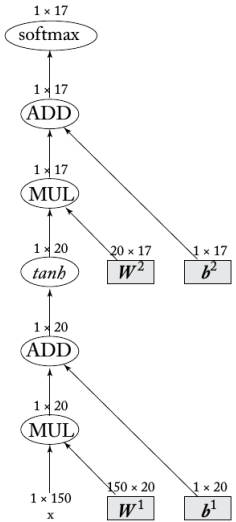
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- Operations, parameters and variables are nodes in a DAG.
- The whole graph should be differentiable.

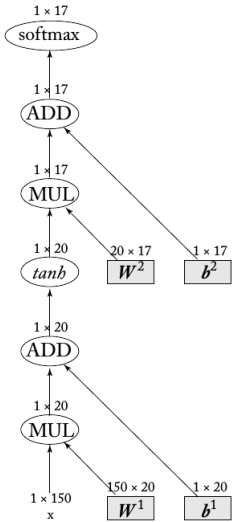
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Think over before the Q&A session / lab session:

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

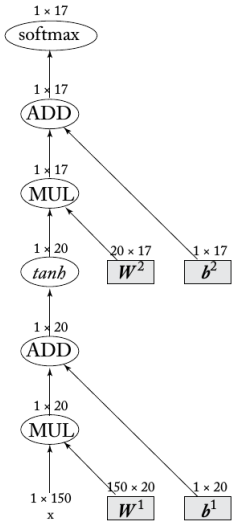
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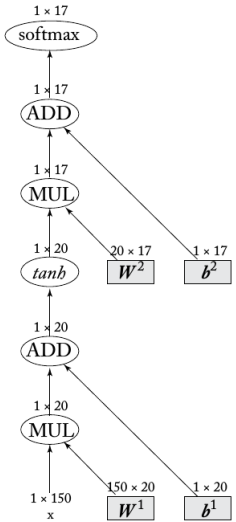
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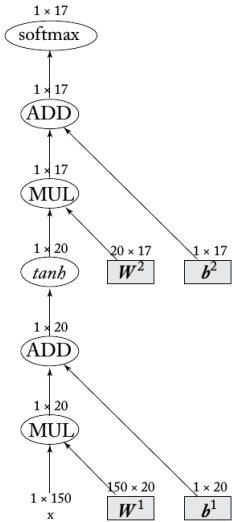
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- **How can you describe what this architecture does?**

Computation graphs



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- 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?

Computation graphs



Forward pass

- Go over all nodes starting from the input;

Computation graphs



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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.

Computation graphs



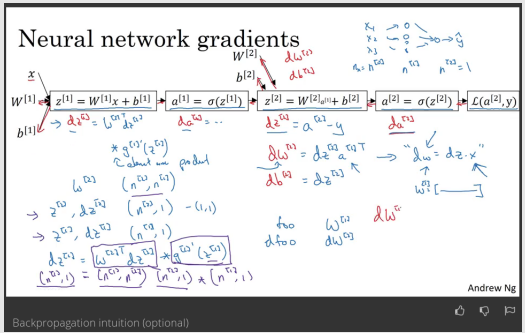
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Computation graphs

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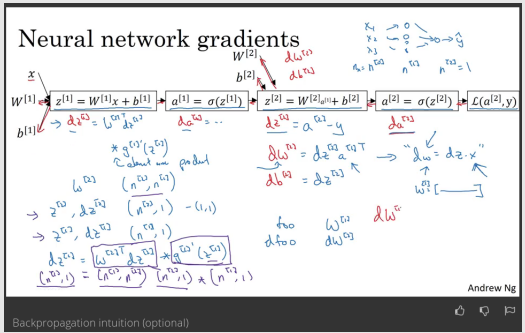
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Computation graphs

Backward pass

- *Back-propagation* is very efficient in terms of computation speed, but very error-prone if done manually...



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

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Neural network toolkits



Software libraries

No lack of open-source deep learning toolkits:

Neural network toolkits



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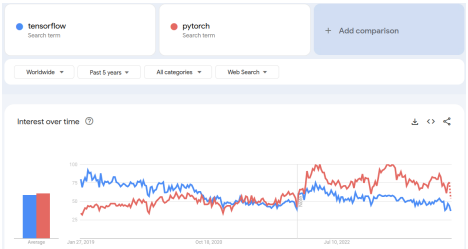
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Every tech giant wants to introduce its own 'definitive deep learning library'.



`https://trends.google.com`

Neural network toolkits



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Neural network toolkits



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- Makes it easy to use deep learning elements in your code.
- `https://pytorch.org/`

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Next week trailer



Dense representations of linguistic features

- Making the discrete world continuous.

Next week trailer



Dense representations of linguistic features

- Making the discrete world continuous.
- Vector semantics.
- Word embeddings.

  Word2vec!

Next week trailer



Dense representations of linguistic features

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- Stay tuned!

References I


Abadi, M., Agarwal, A., Barham, P., Brevdo, E., Chen, Z., Citro, C., Corrado, G. S., Davis, A., Dean, J., Devin, M., Ghemawat, S., Goodfellow, I., Harp, A., Irving, G., Isard, M., Jia, Y., Jozefowicz, R., Kaiser, L., Kudlur, M., Levenberg, J., Mané, D., Monga, R., Moore, S., Murray, D., Olah, C., Schuster, M., Shlens, J., Steiner, B., Sutskever, I., Talwar, K., Tucker, P., Vanhoucke, V., Vasudevan, V., Viégas, F., Vinyals, O., Warden, P., Wattenberg, M., Wicke, M., Yu, Y., and Zheng, X. (2015).
TensorFlow: Large-scale machine learning on heterogeneous systems.
Software available from tensorflow.org.


Bradbury, J., Frostig, R., Hawkins, P., Johnson, M. J., Leary, C., Maclaurin, D., Necula, G., Paszke, A., VanderPlas, J., Wanderman-Milne, S., and Zhang, Q. (2018).
JAX: composable transformations of Python+NumPy programs.


Kumar, S. and Tsvetkov, Y. (2018).
Von Mises-Fisher loss for training sequence to sequence models with continuous outputs.
In International Conference on Learning Representations.

References II


Paszke, A., Gross, S., Chintala, S., and Chanan, G. (2017).
Pytorch: Tensors and dynamic neural networks in Python with strong GPU acceleration.


Rumelhart, D. E., Hinton, G. E., and Williams, R. J. (1986).
Learning representations by back-propagating errors.
Nature, 323(6088):533.