CMPT 733

Advanced Topics in Deep Learning

Sequence learning, Sentiment analysis, Word2Vec, DL-Vis

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March 17, 2018

Overview

- Deep learning approaches for sequence learning with RNNs
- Natural language processing (NLP) with Python
  - Sentiment analysis using NLTK
  - Word embeddings
- Visualization for Deep Learning

Recap: Choosing architecture family

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- No structure $\rightarrow$ fully connected

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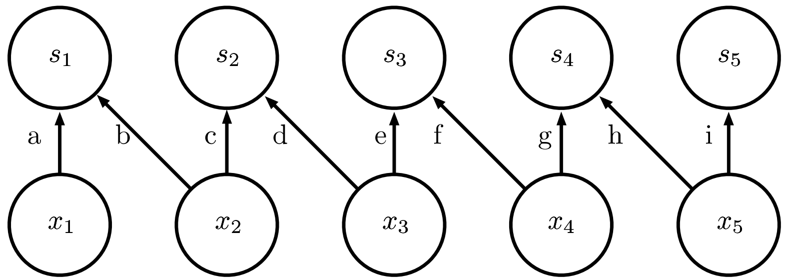
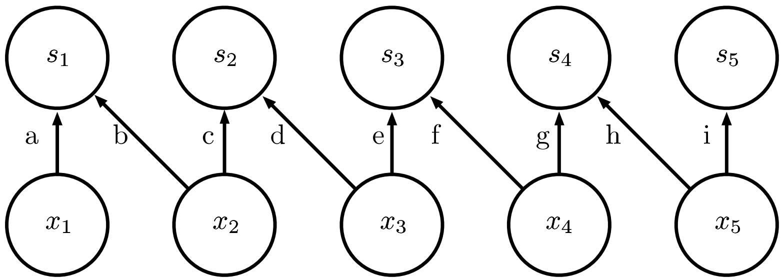
- No structure $\rightarrow$ fully connected
- Spatial structure $\rightarrow$ convolutional
- Sequential structure $\rightarrow$ recurrent

Types of connectivity



Local connection:
like convolution,
but no sharing

Types of connectivity



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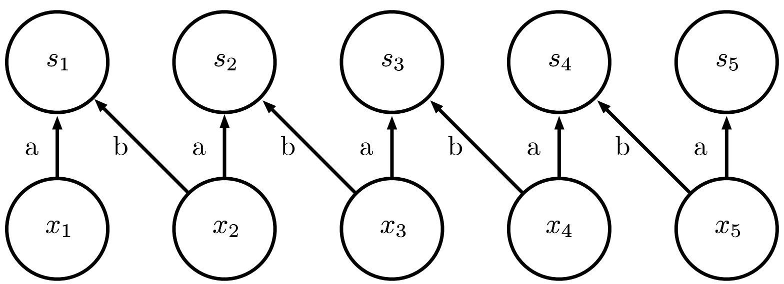
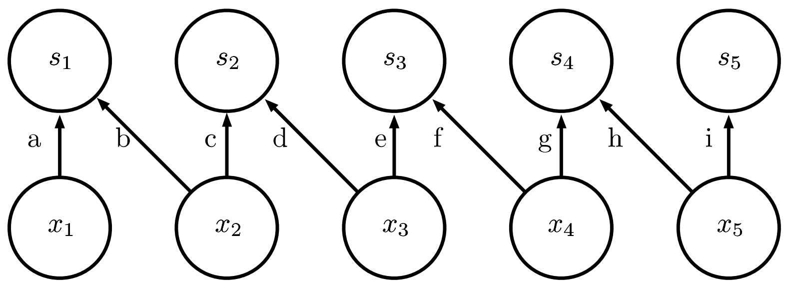


Convolution

Types of connectivity



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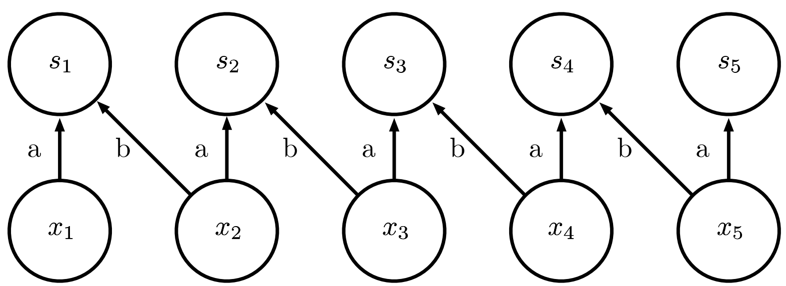
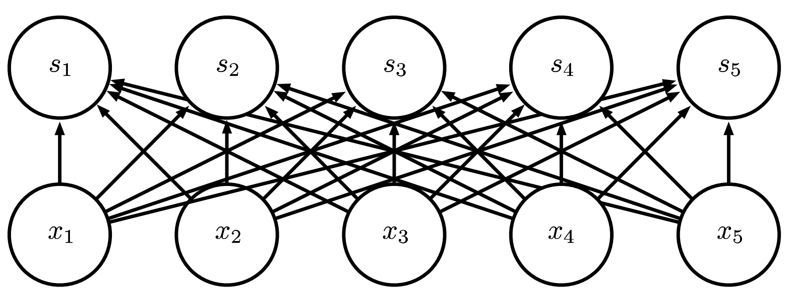


Convolution



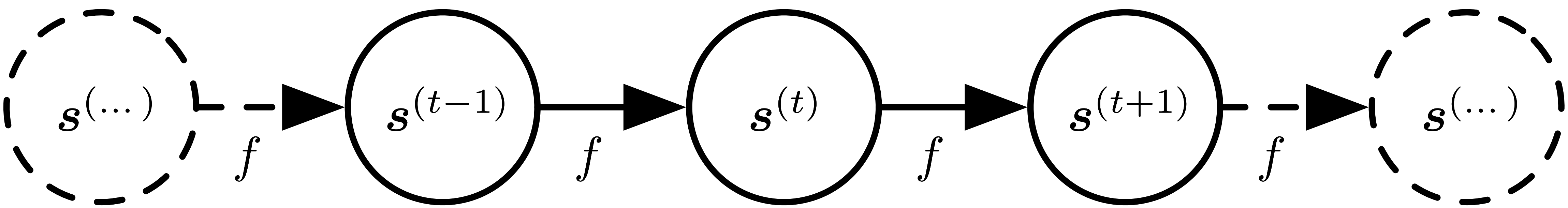
Fully connected

[Goodfellow, Bengio, Courville 2016]

Sequence Modeling with Recurrent Nets

Classical Dynamical Systems

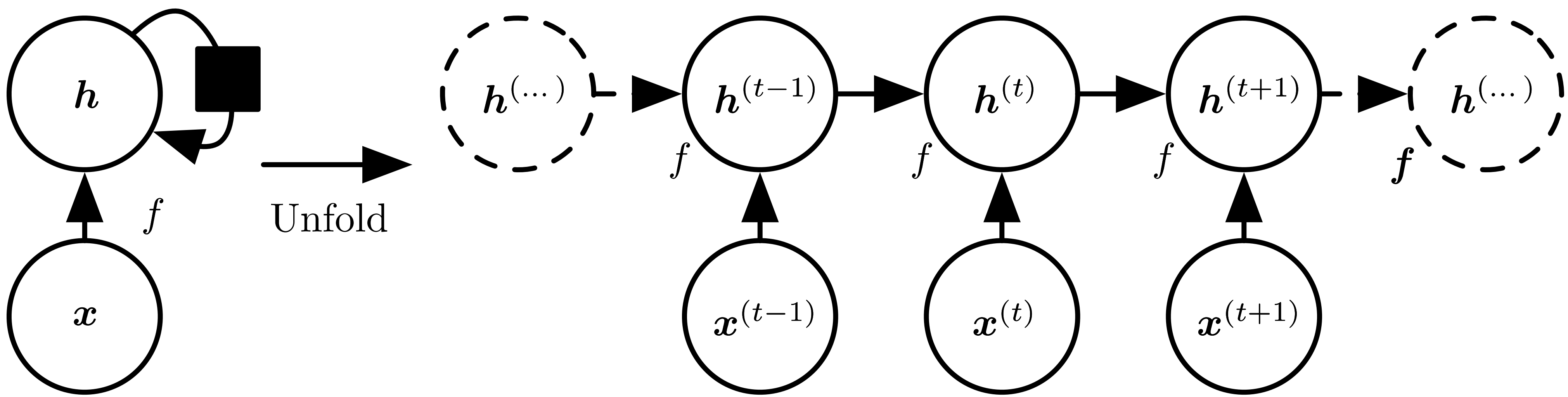
- Recurrent network is kind of dynamical system that is updated in discrete steps over time
- Function f takes input from time t to output at time t+1
- Rules persis across time



[Goodfellow, Bengio, Courville 2016]

Unfolding Computation Graphs

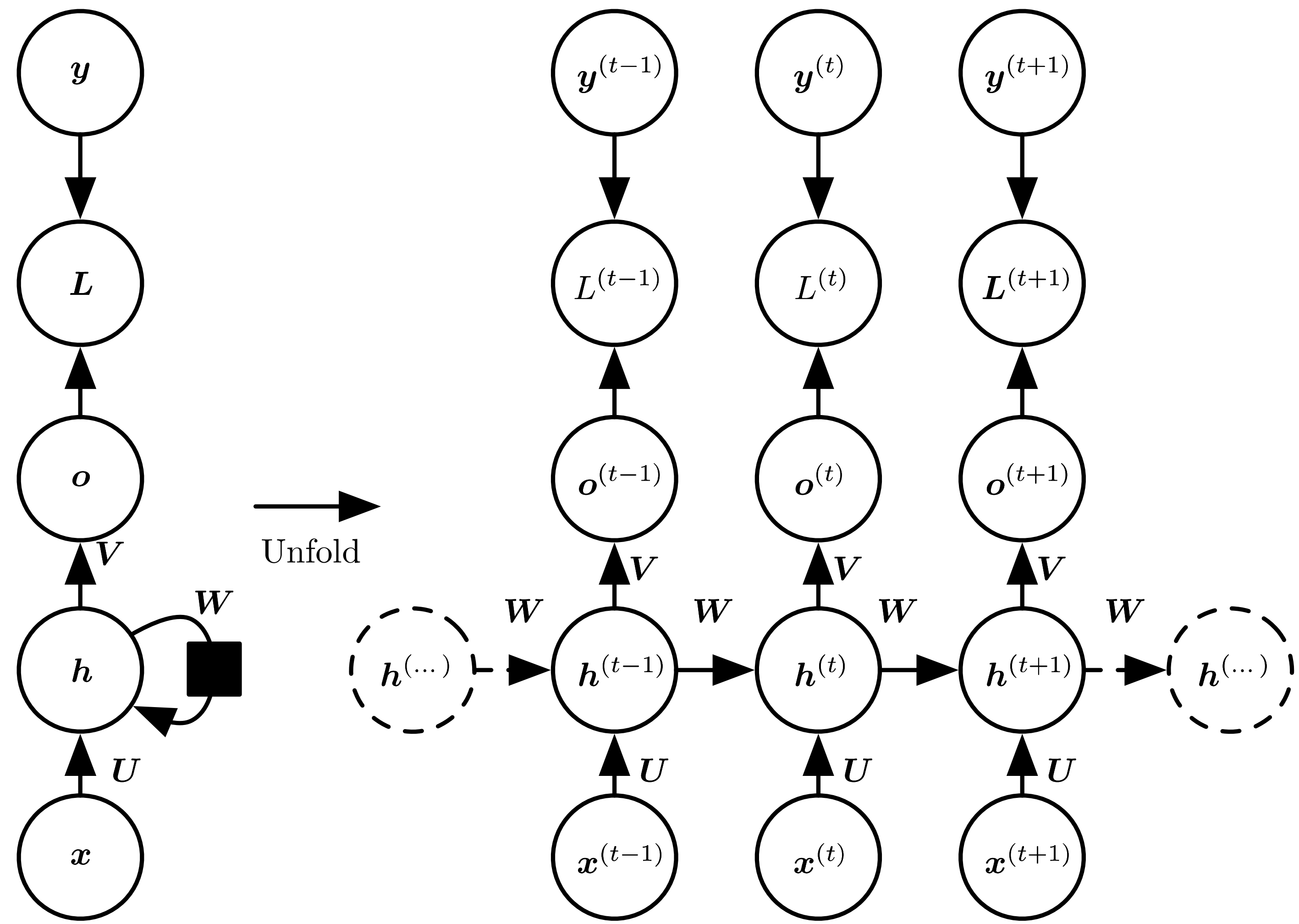
- Recurrent graph can be unfolded, where hidden state h is influencing itself
- Backprop through time is just backprop on unfolded graph



[Goodfellow, Bengio, Courville 2016]

Recurrent Hidden Units

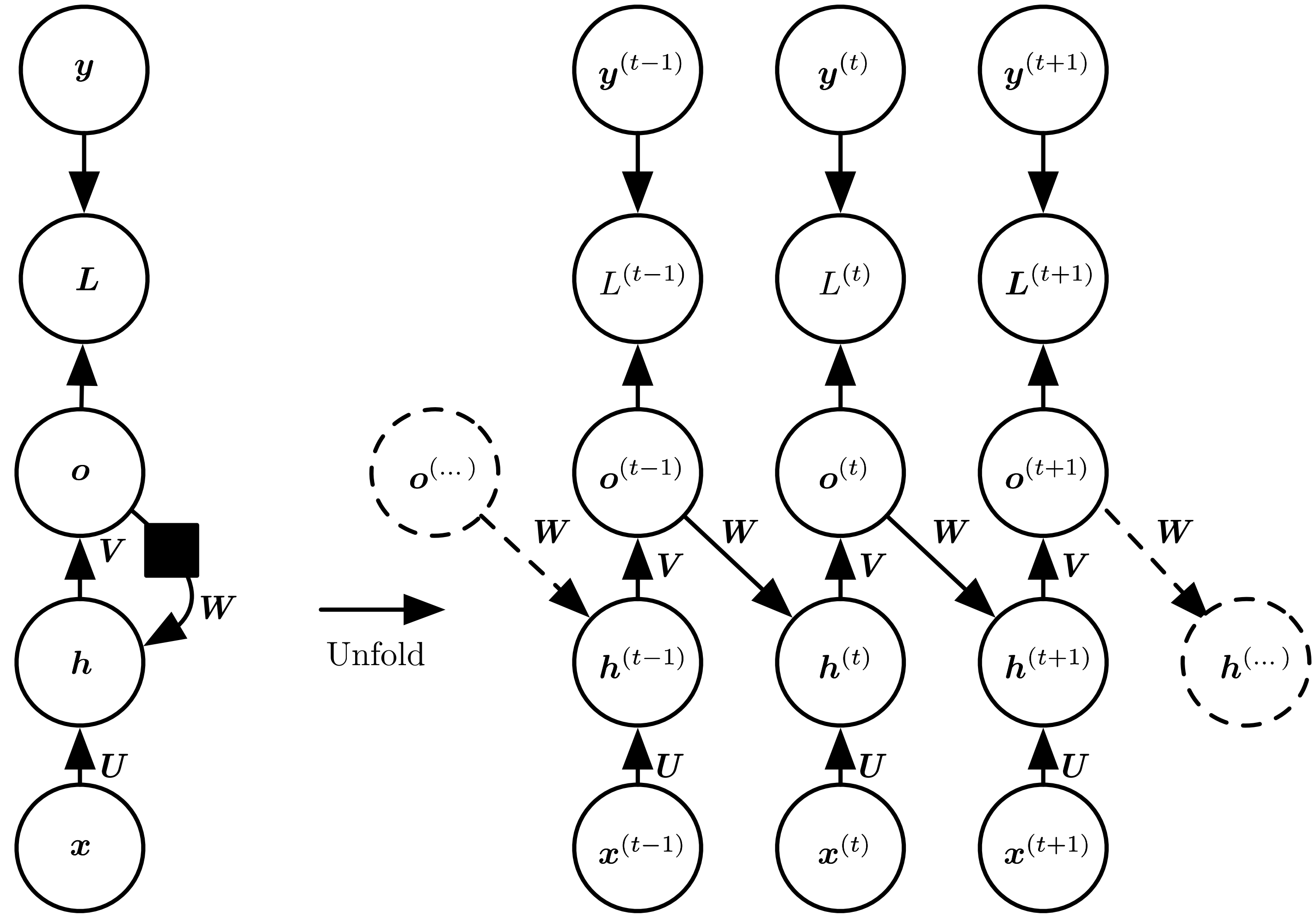
- More than one layer



[Goodfellow, Bengio, Courville 2016]

Recurrence only through output

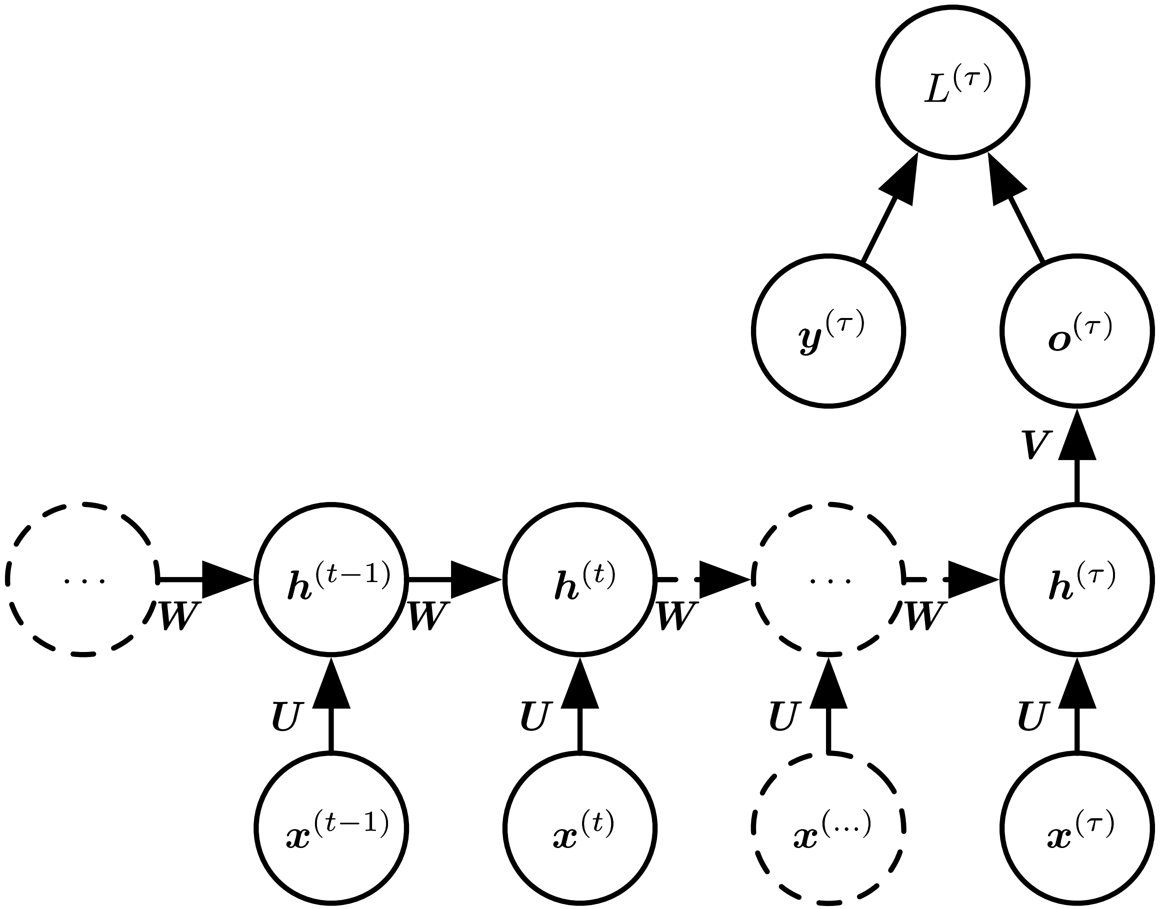
- Avoid backprop through time
- Train using teacher forcing technique
  - Backprop stops when it reaches y(t-1) via o(t-1)



[Goodfellow, Bengio, Courville 2016]

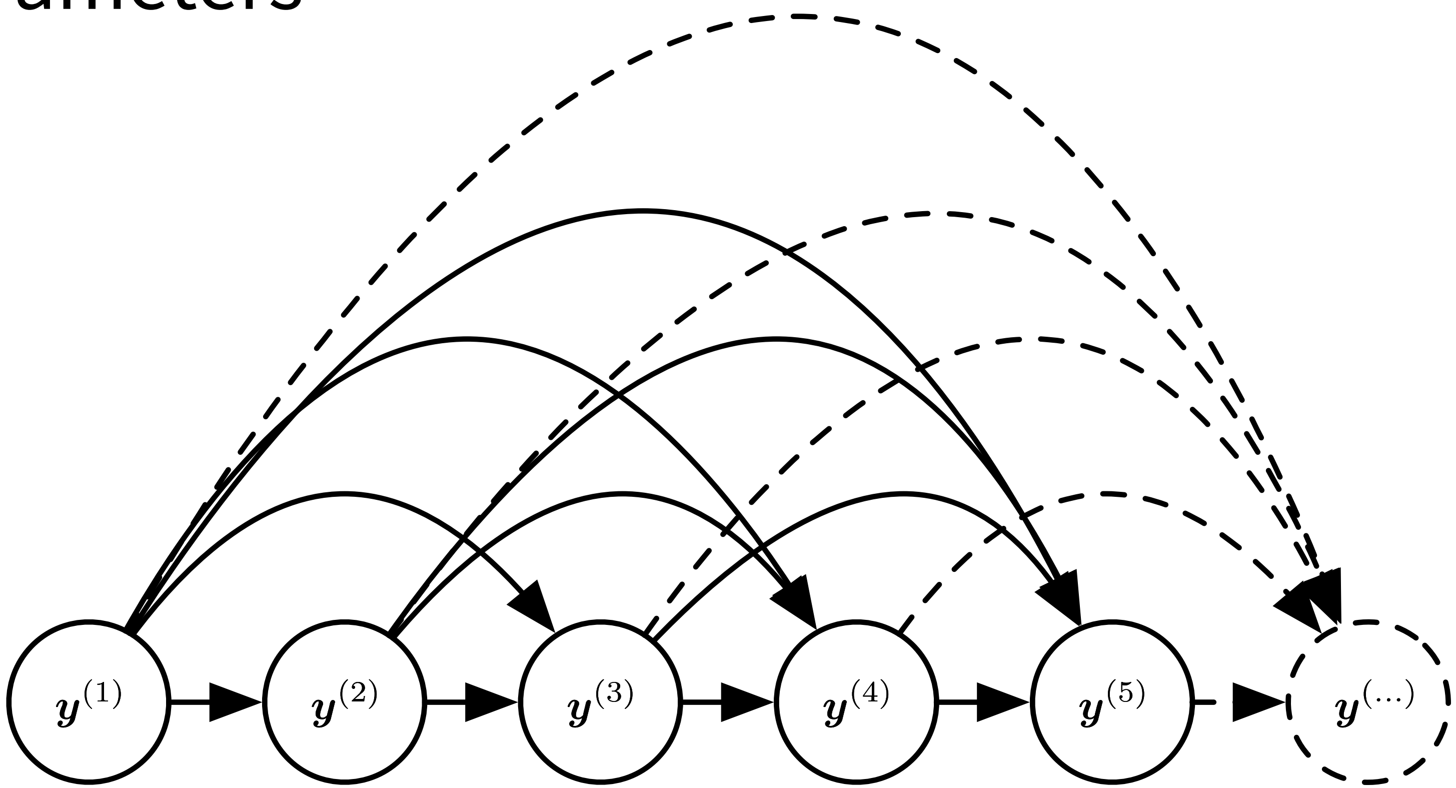
Sequence Input, Single Output

- E.g. sentiment analysis of some review text



Fully Connected Graphical Model

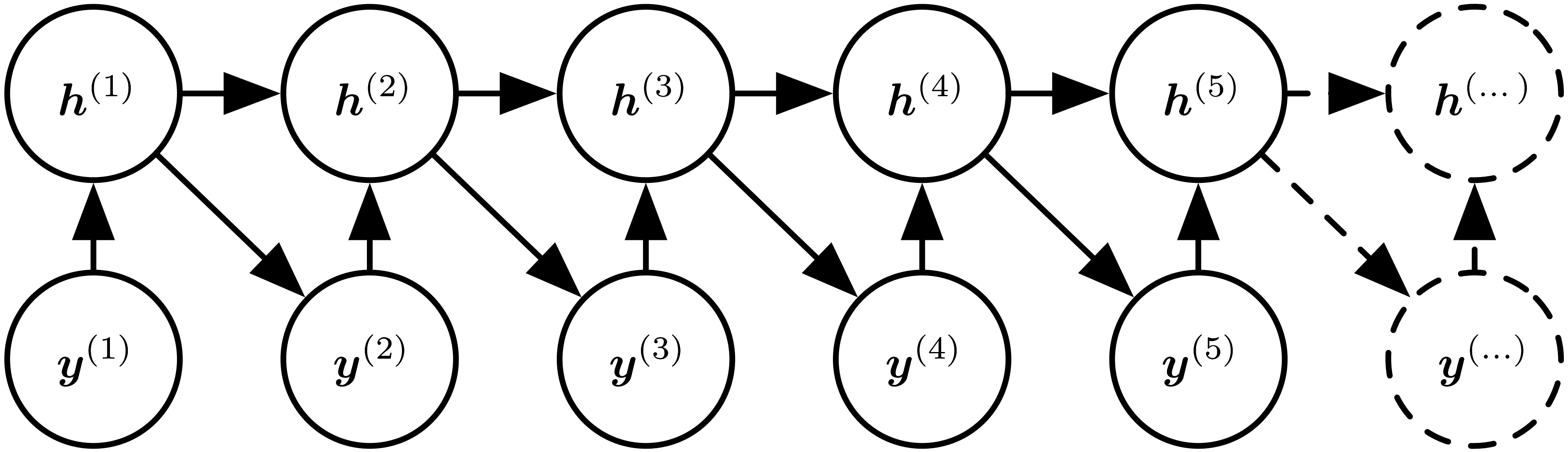
- Too many dependencies among variables, if each has its own set of parameters



[Goodfellow, Bengio, Courville 2016]

RNN Graphical Model

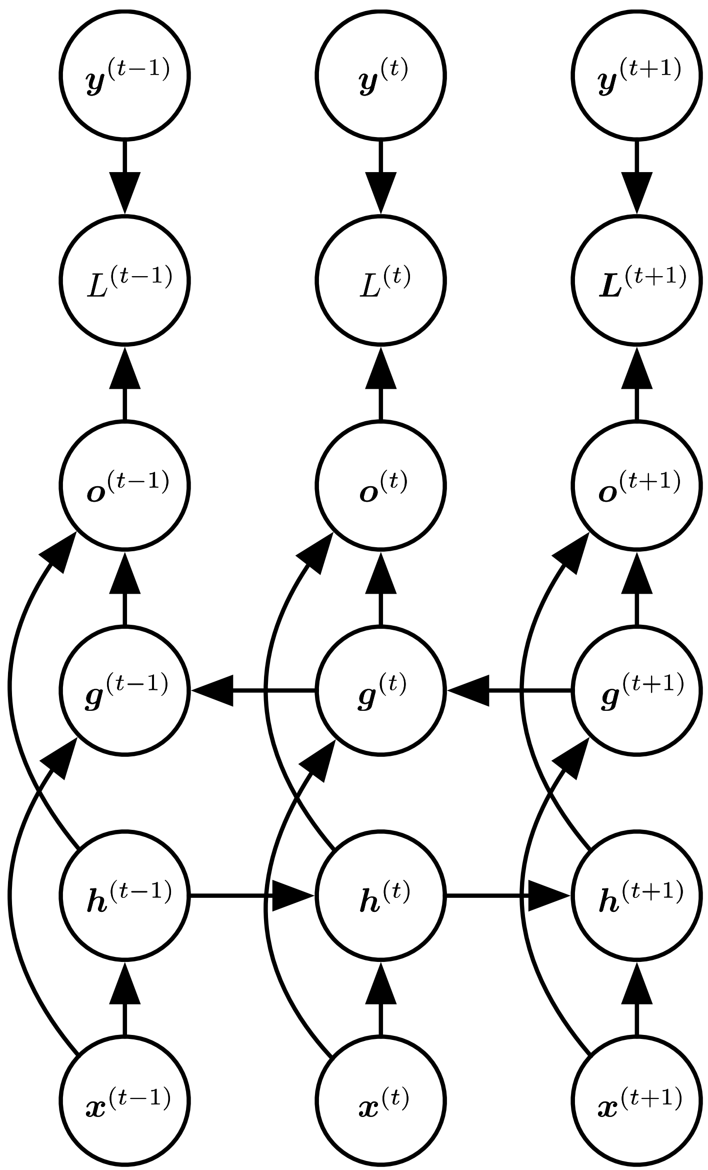
- Organize variables according to time with single update rule
- Finite set of relationships may extend to infinite sequences
- h acts as "memory state" summarizing relevant history



[Goodfellow, Bengio, Courville 2016]

Bidirectional RNN

- Later information may be used to reassess previous observations

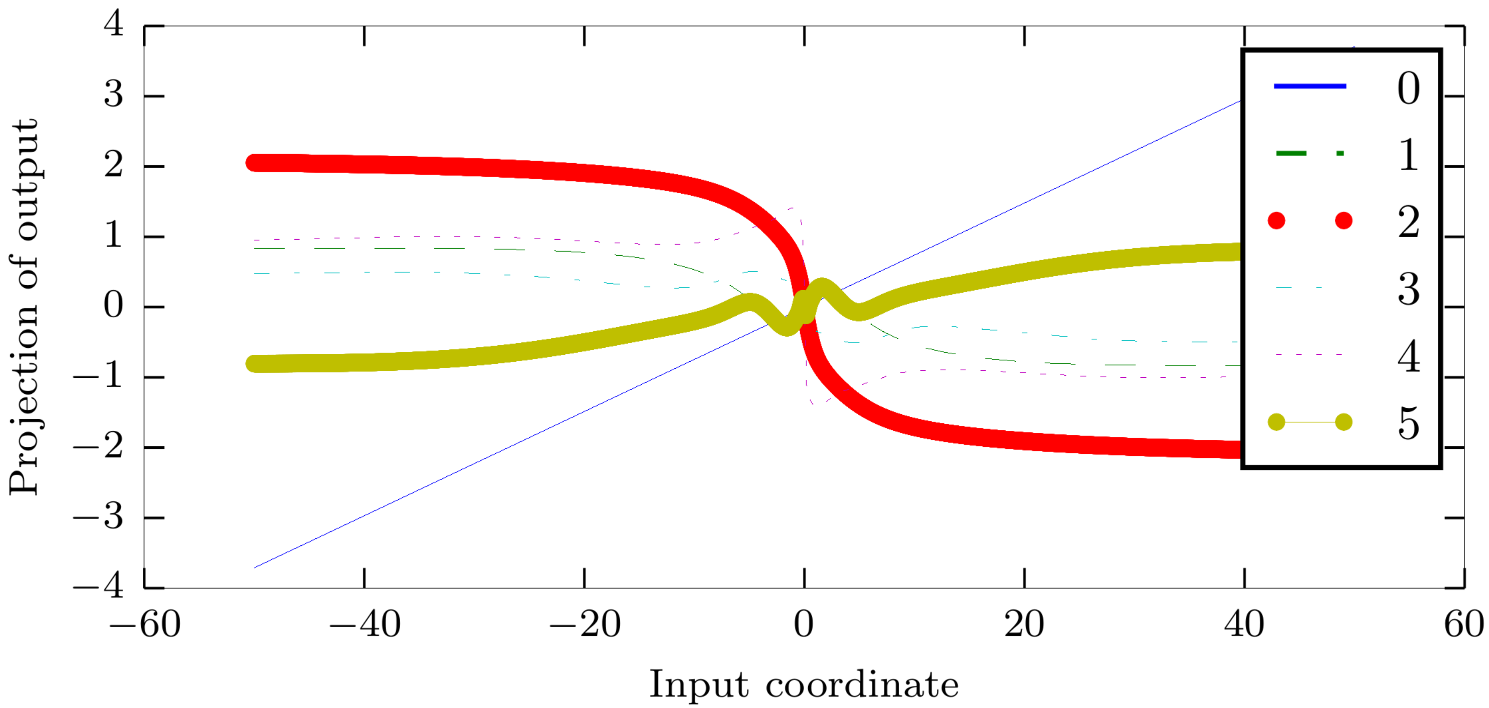


[Goodfellow, Bengio, Courville 2016]

Exploding Gradients from Function Composition

- Example: one input variable, color encodes number of times RNN update rule is run

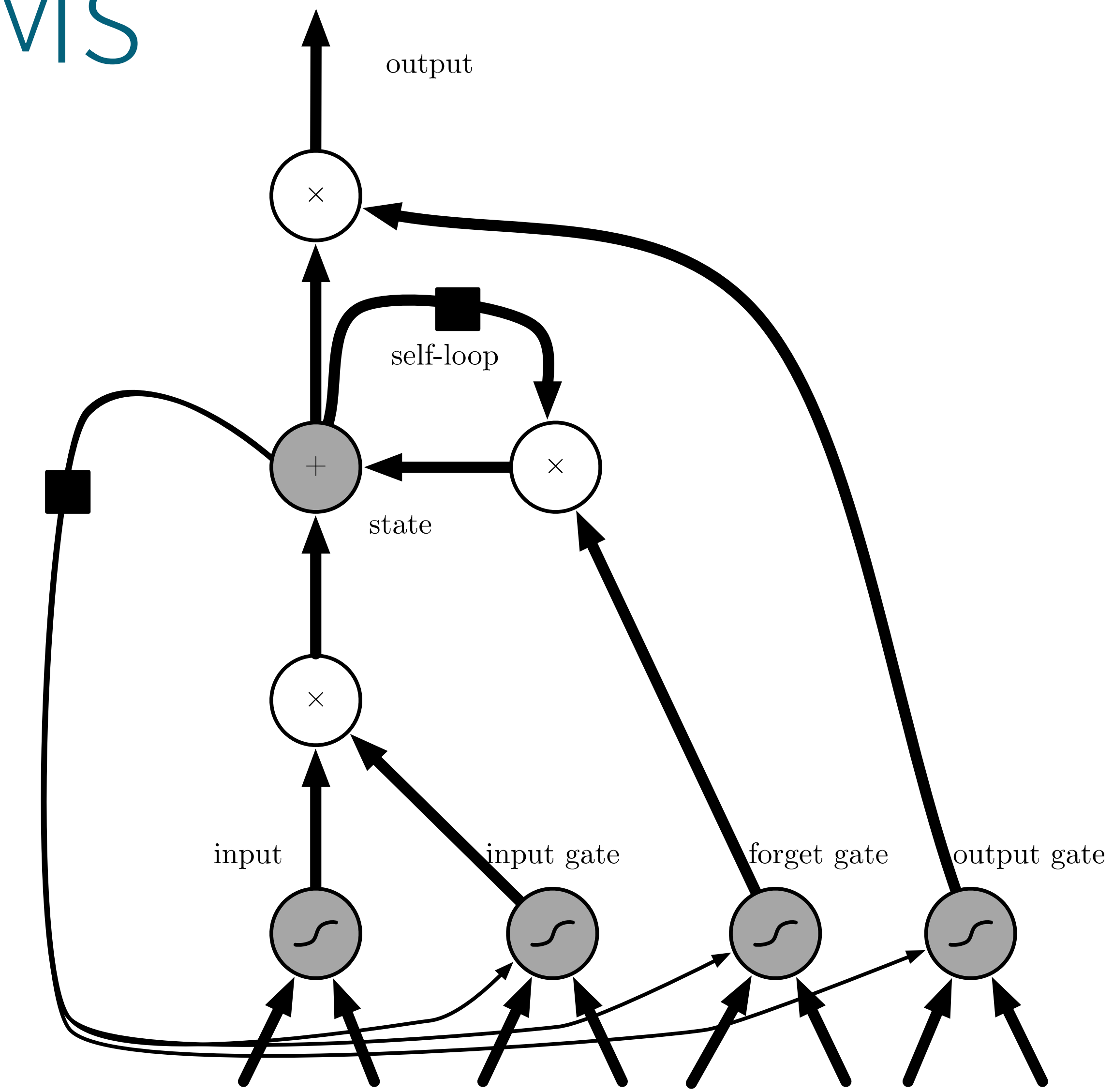
  - Exponentiation of weights from one time step to the next
  - Feed-forward nets don't have this problem, due to different weights in each layer



[Goodfellow, Bengio, Courville 2016]

LSTMs

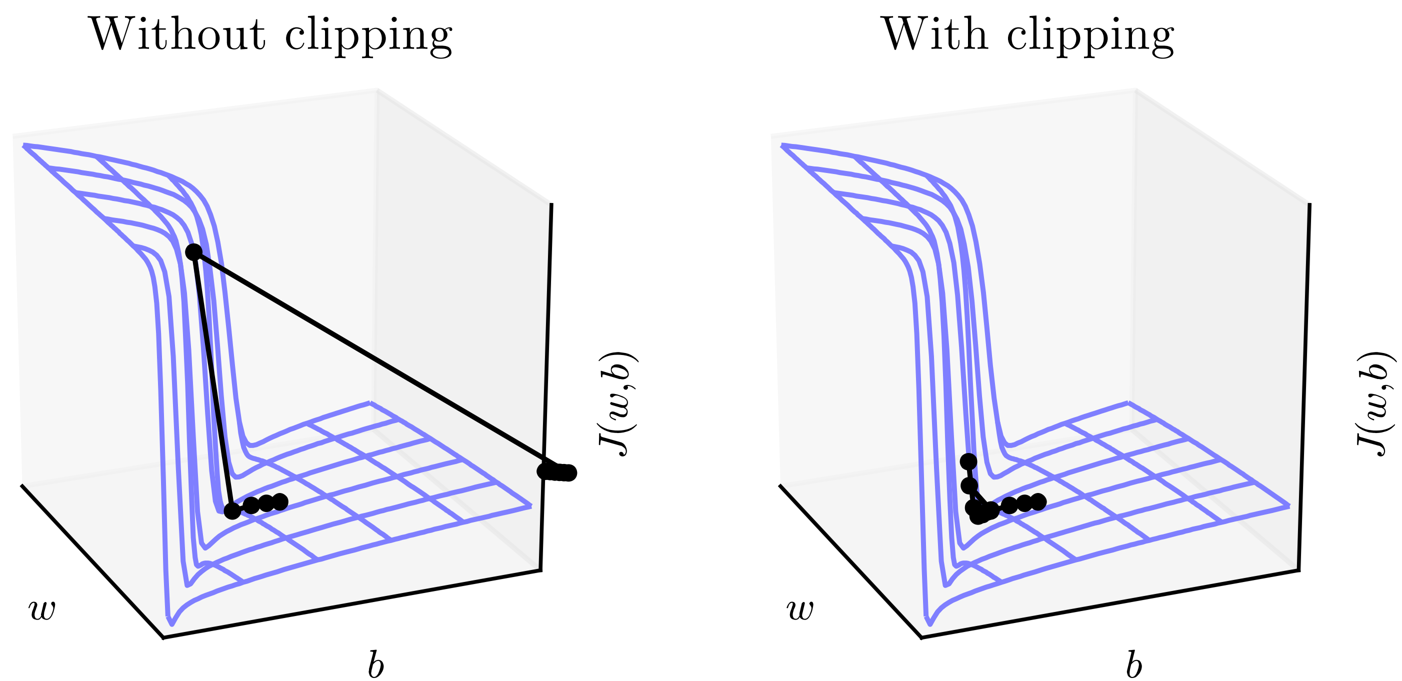
- Use addition over time instead of multiplication



[Goodfellow, Bengio, Courville 2016]

Gradient Clipping

- Add learning rate time gradient to update parameters
- Believe direction of gradient, but not its magnitude



Sentiment Analysis
Word embeddings

Sentiment Analysis

- Computational study of opinions, sentiments, subjectivity, evaluations, attitudes, appraisal, affects, views, emotions, etc., expressed in text

  [B. Liu 2011]

- Aka Opionion mining

Step A: Text processing

- Break up text into sentences
- Tokenize words
- Remove stop words [I, had, the, a, as, there]
- What other preprocessing could be useful?

B1: Words -> hash indices

- Each word is a string
- Hash each string to a number

Problems:

- Large vocab leads to large vectors -> store as sparse vec

B2: Doc -> word count vector

- Term frequency (TF)
  - Count the number of occurrences of each string in each doc
- Frequent words with less meaning dominate
- Scale down with a measure of ubiquity
  - inverse doc frequency (IDF)
- Semantically equivalent words are **not** grouped together

Better: Use Word2Vec

Distributional Hypothesis

- Word semantics are taken into account
- Words that are used and occur in same context tend to support the same meaning
- “Judge a word by the company it keeps.”
- Dense word representation (word2vec, see Spark ML)

C: Document -> average vectors

- Word vectors -> clusters, docs -> avg cluster vectors
- Use k-means, cluster groups synonyms or topics

D: Regression / Classification

- Linear regression: star rating
- Logistic regression: likes, smiley types, etc.

Sentiment using LSTMs

- Stanford Sentiment Treebank

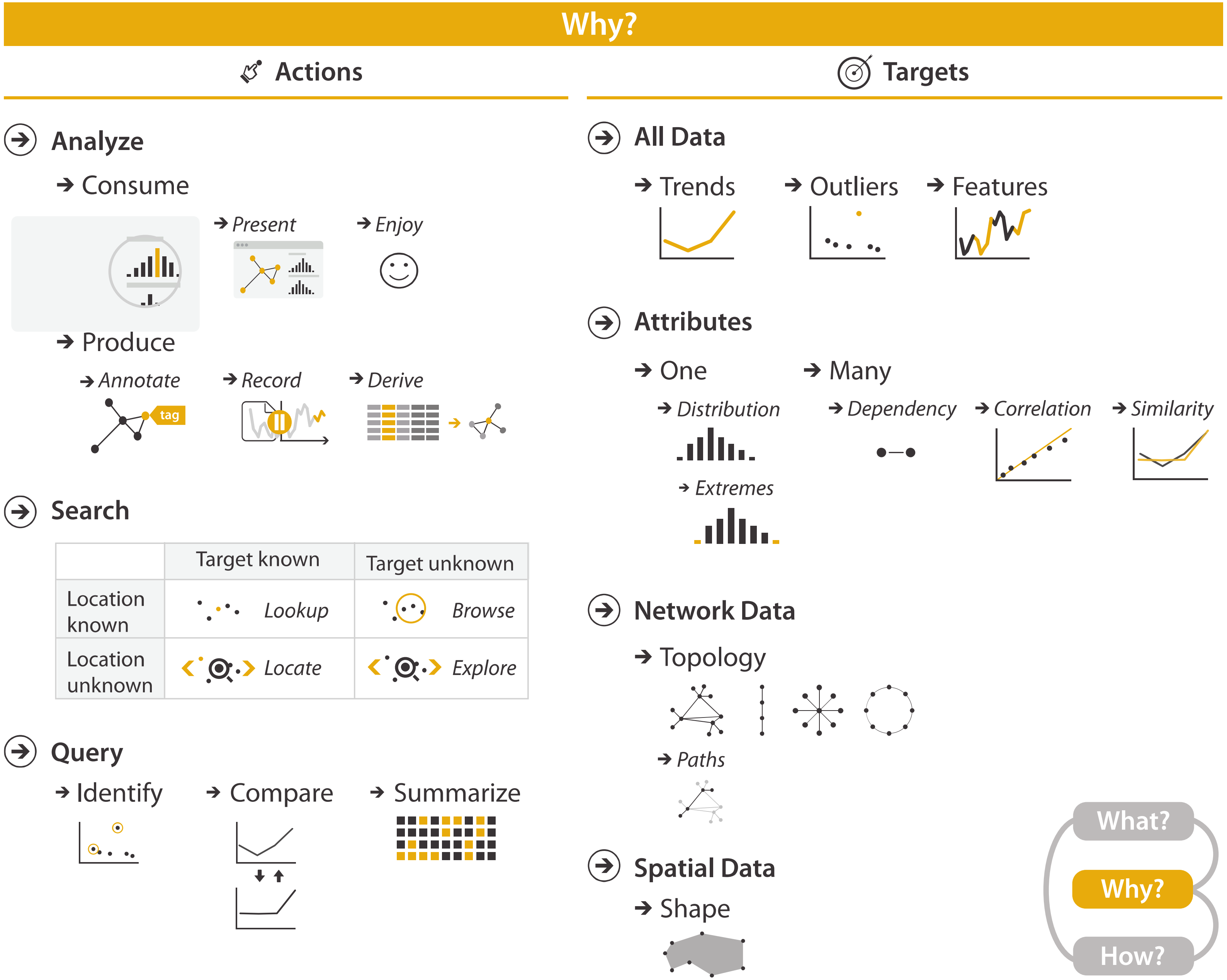
  https://nlp.stanford.edu/sentiment/treebank.html

- Simple LSTM implementation using word2vec:

  https://github.com/git-steb/pytorch-sentiment-classification

  fork of: https://github.com/clairett/pytorch-sentiment-classification/

Visualization Recap:
Data, Task, and Encoding



Tasks

- Actions
  - Analyze
  - Search
  - Query
- Targets
  - Item & Attributes
  - Topology & Shape
  - **Models of Data**

[T. Munzner, 2014]

Visualization for ML

- **Tensorboard: Visualizing Learning**
- How to use t-SNE efficiently

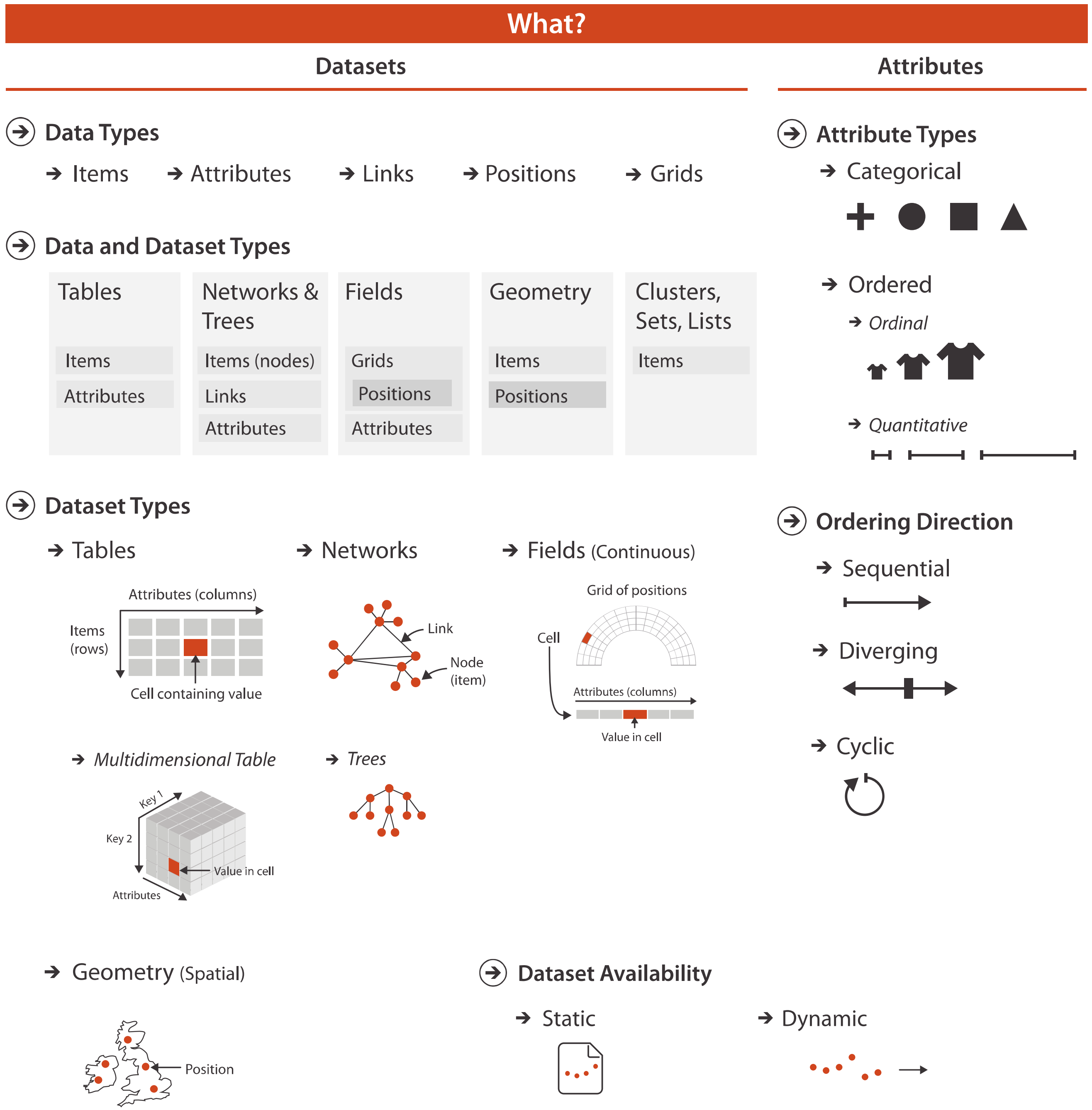
Model visualization

- **LSTM-Vis**: http://lstm.seas.harvard.edu/client/index.html
- Building blocks of interpretability
- SHAP (SHapley Additive exPlanations)
- Lime: Explaining the predictions of any ML classifier

Sources

- I. Goodfellow, Y. Bengio, A. Courville “Deep Learning” MIT Press 2016 [link]
- Apala Guha’s slides from 2017-CMPT 733

Extra Slides for Vis Recap



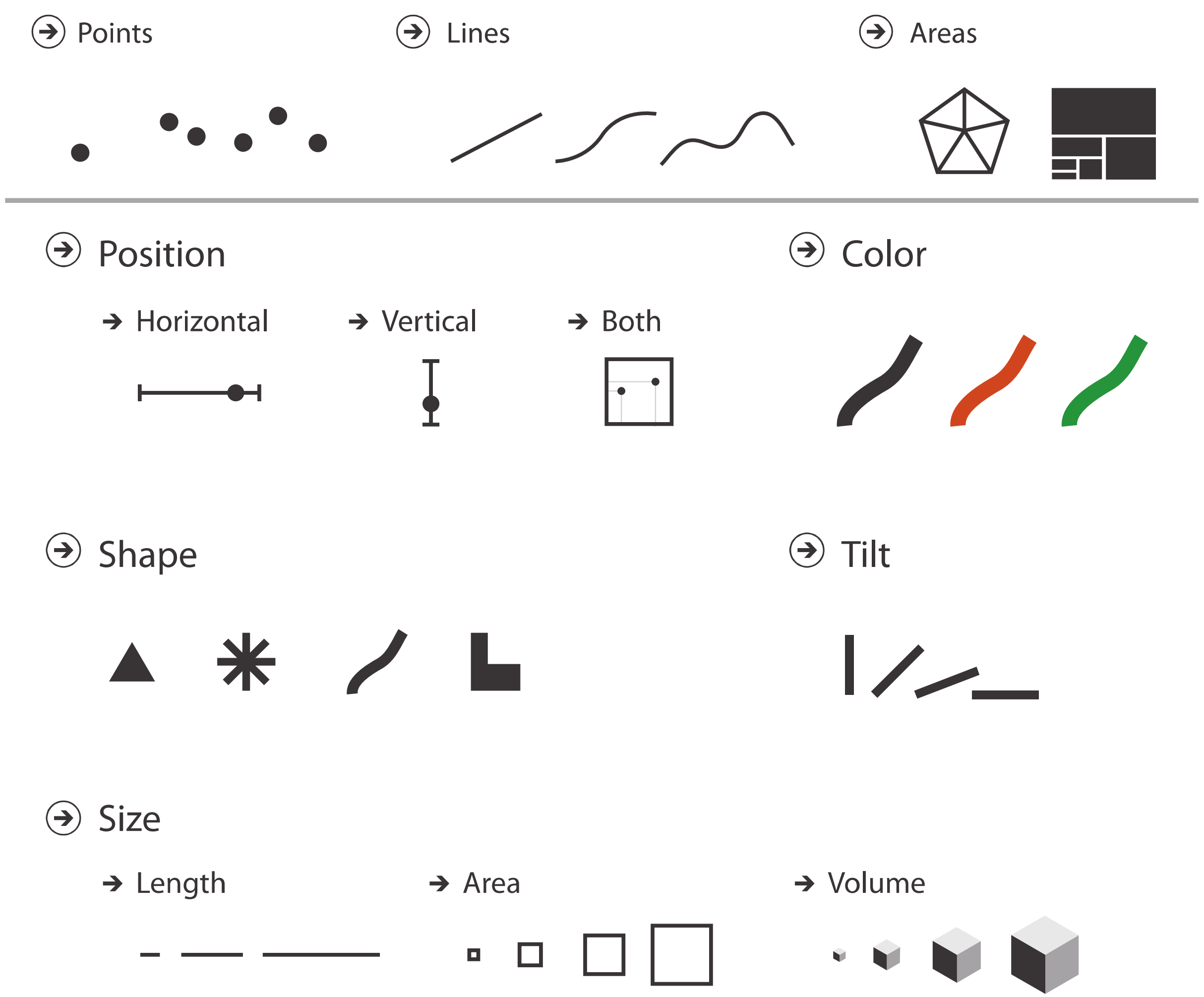
Data Types

- Items and attributes as rows and columns of tables
- Position and time are special attributes
- Spatial data on grids makes computation easier

[T. Munzner, 2014]

Visual Encoding – How?

- Marks
  - Geometric primitives
- Channels
  - Appearance of marks
  - Redundant coding with multiple channels possible



[T. Munzner, 2014]