Practical Methodology for Deploying Machine Learning

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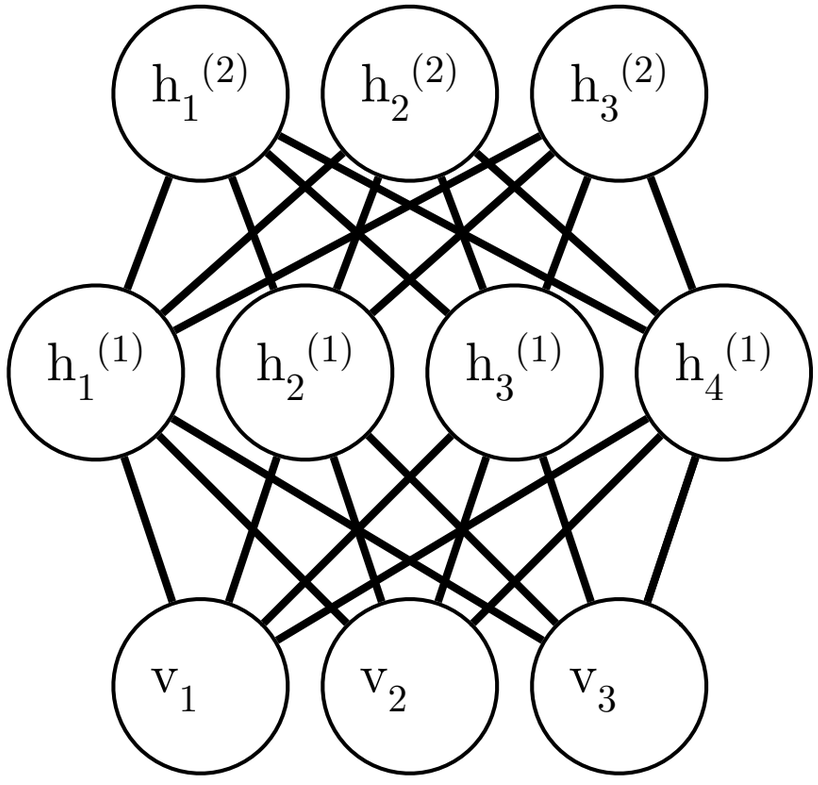
(An homage to "Advice for Applying Machine Learning" by Andrew Ng)

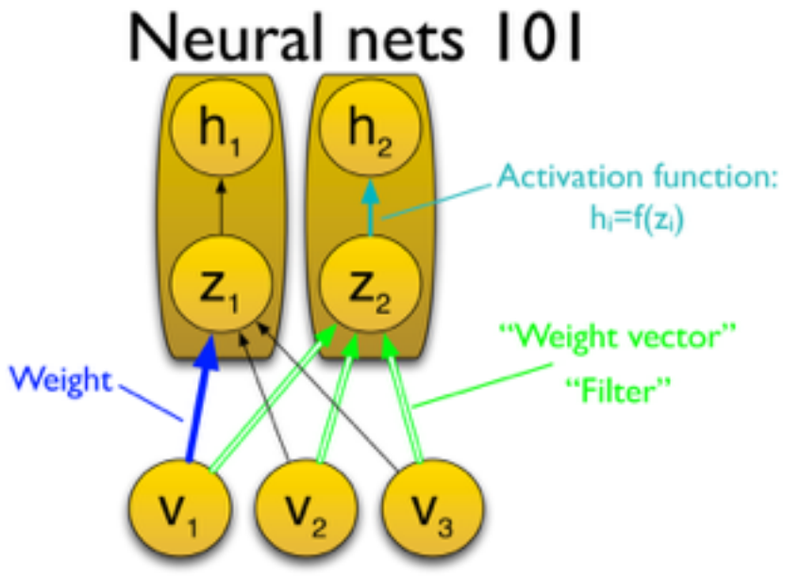
What drives success in ML?

Arcane knowledge of dozens of obscure algorithms?

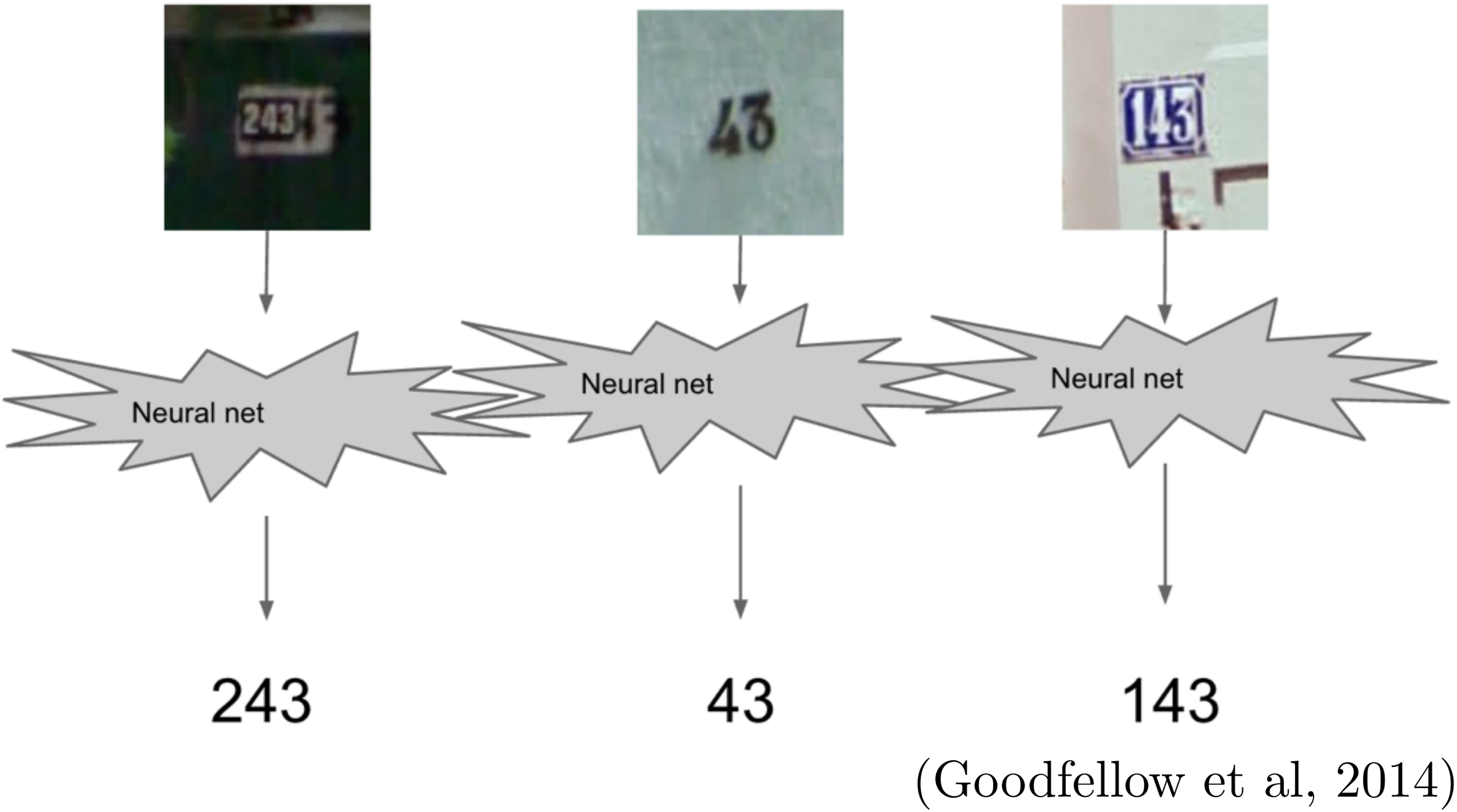


Mountains of data?

Knowing how to apply 3-4 standard techniques?



Street View Transcription



(Goodfellow et al, 2014)

3 Step Process

- Use needs to define metric-based goals
- Build an end-to-end system
- Data-driven refinement

Identify needs

- High accuracy or low accuracy?
- Surgery robot: high accuracy
- Celebrity look-a-like app: low accuracy

Choose Metrics

- Accuracy? (% of examples correct)
- Coverage? (% of examples processed)
- Precision? (% of detections that are right)
- Recall? (% of objects detected)
- Amount of error? (For regression problems)

End-to-end system

- Get up and running ASAP
- Build the simplest viable system first
- What baseline to start with though?
  - Copy state-of-the-art from related publication

Deep or not?

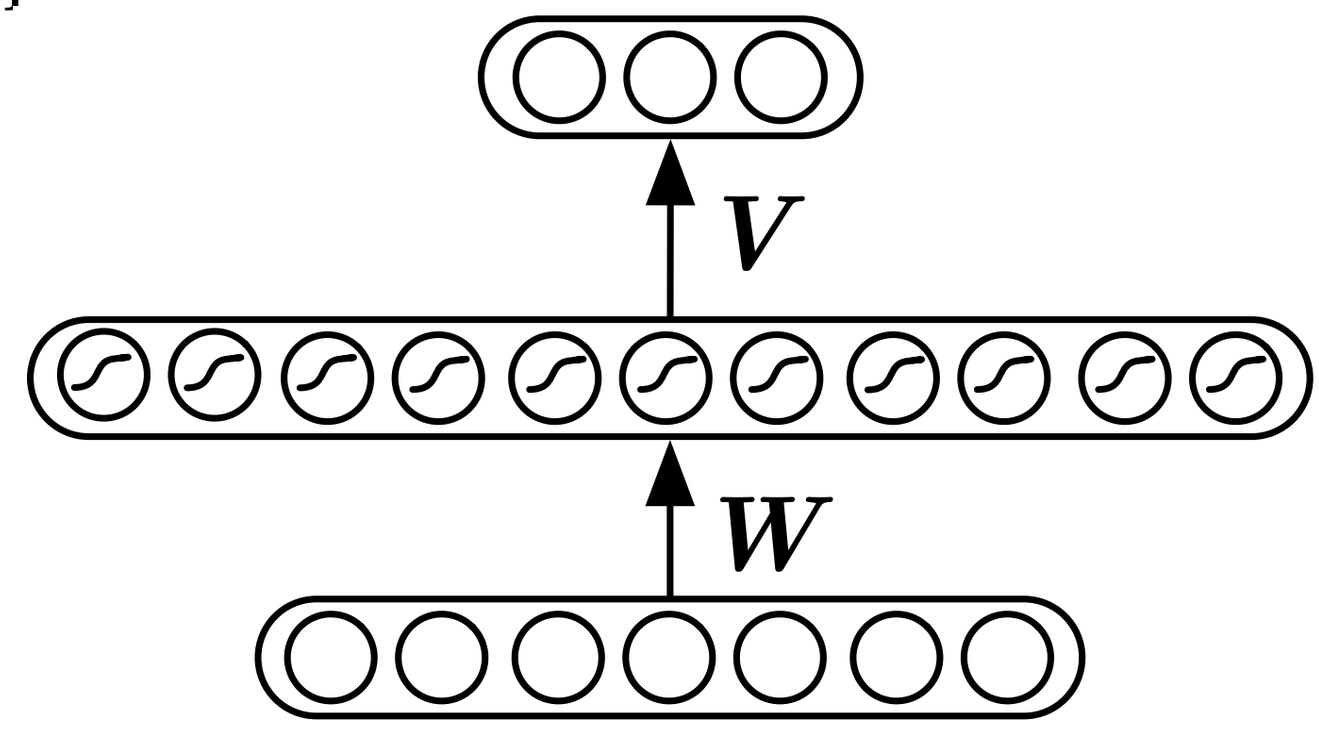
- Lots of noise, little structure -> not deep
- Little noise, complex structure -> deep
- Good shallow baseline:
  - *Use what you know*
  - Logistic regression, SVM, boosted tree are all good

What kind of deep?

- No structure -> fully connected
- Spatial structure -> convolutional
- Sequential structure -> recurrent

Fully connected baseline

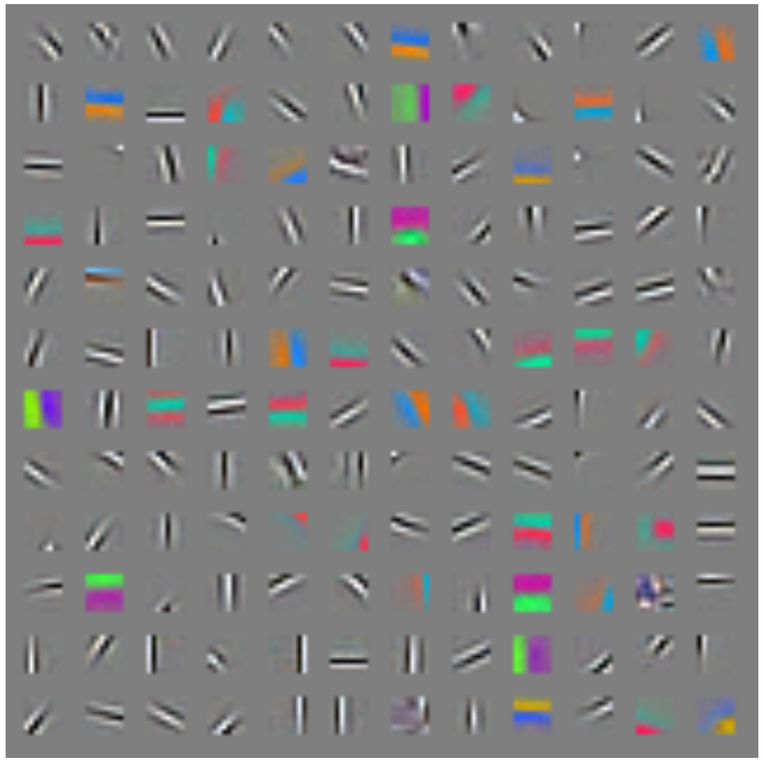
- 2-3 hidden layer feedforward network
- AKA "multilayer perceptron"
- Rectified linear units
- Dropout
- SGD + momentum



Convolutional baseline

- Inception

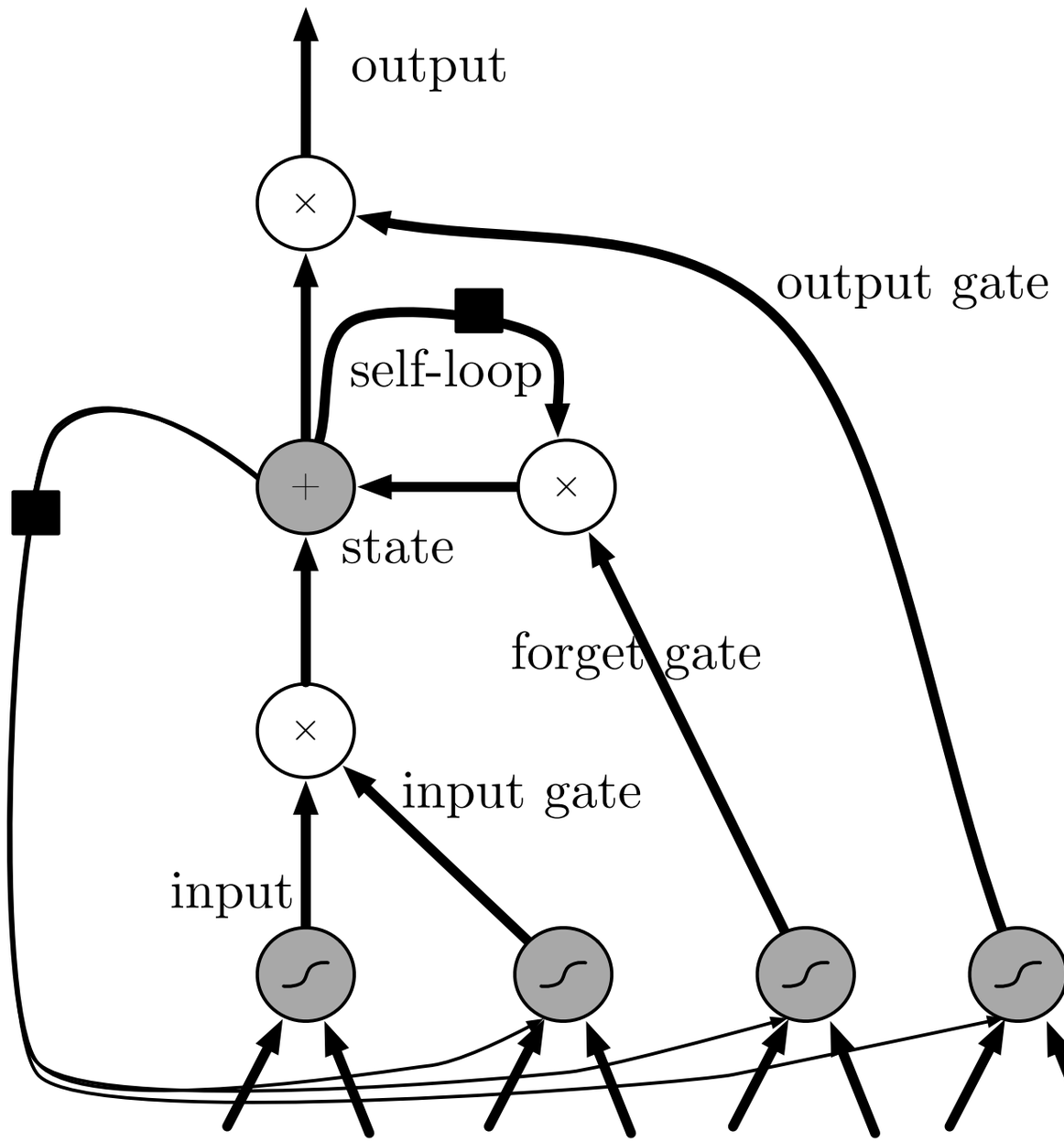
- Batch normalization



- Fallback option:
  - Rectified linear convolutional net
  - Dropout
  - SGD + momentum

Recurrent baseline

- LSTM
- SGD
- Gradient clipping
- High forget gate bias



Data driven adaptation

- Choose what to do based on data
- Don't believe hype
- Measure train and test error
  - "Overfitting" versus "underfitting"

High train error

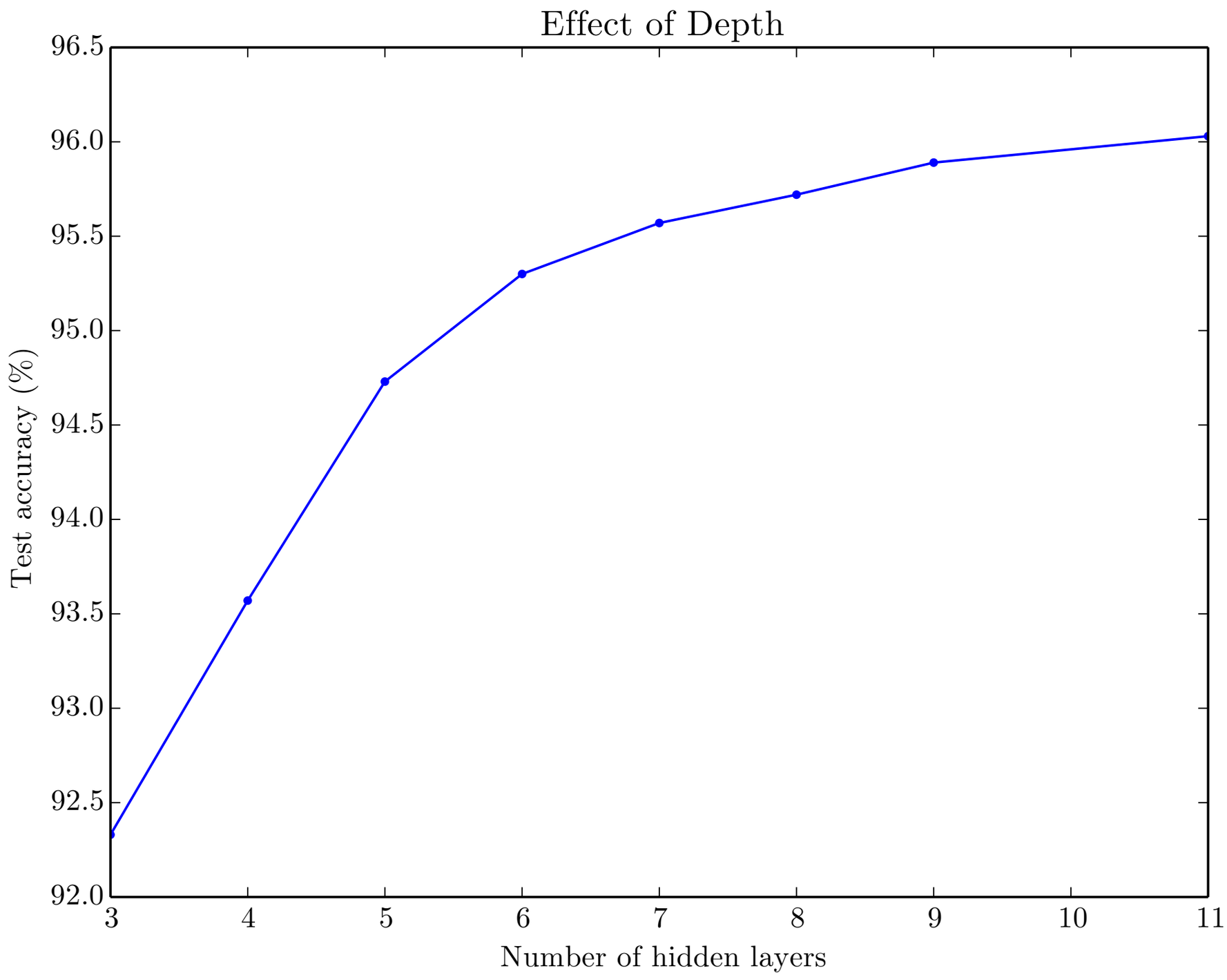
- Inspect data for defects
- Inspect software for bugs
    - Don't roll your own unless you know what you're doing
- Tune learning rate (and other optimization settings)
- Make model bigger

Checking data for defects

- Can a human process it?

26624

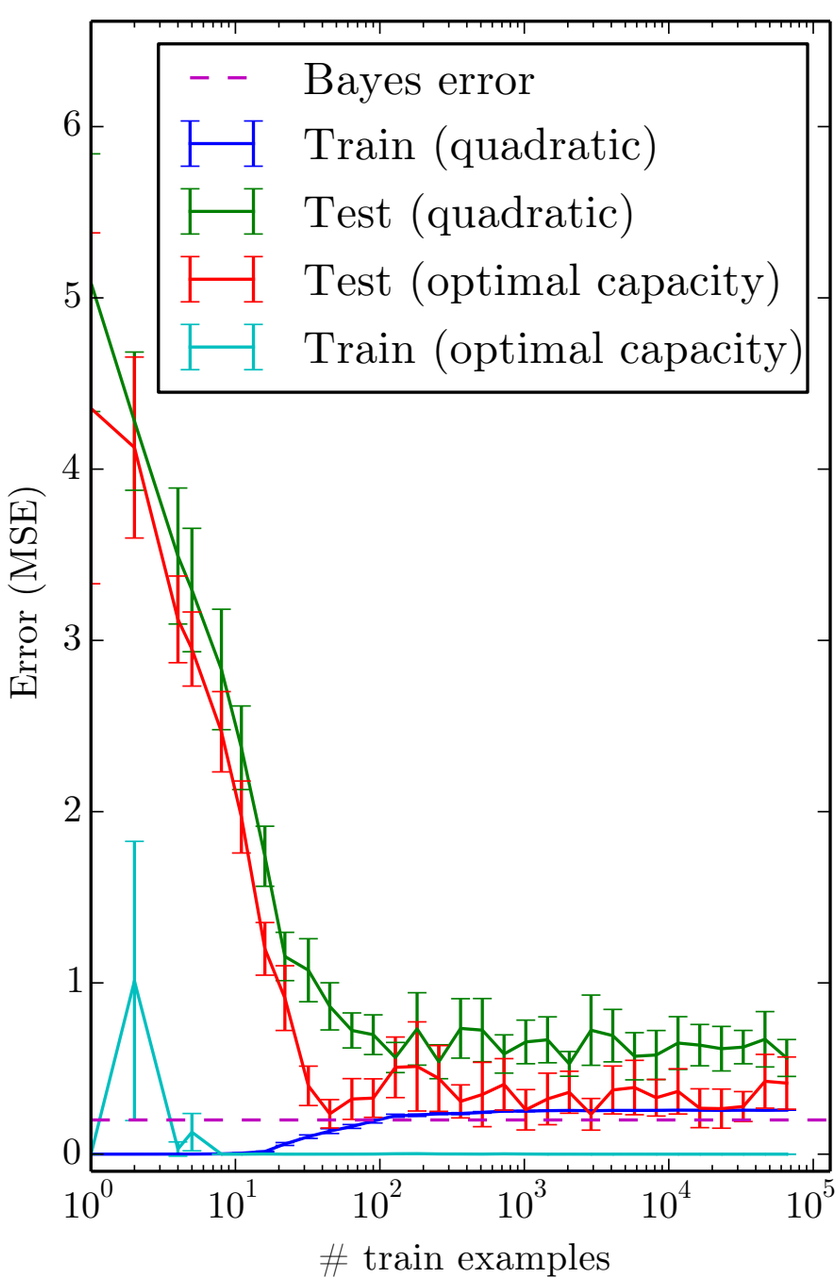
Increasing depth

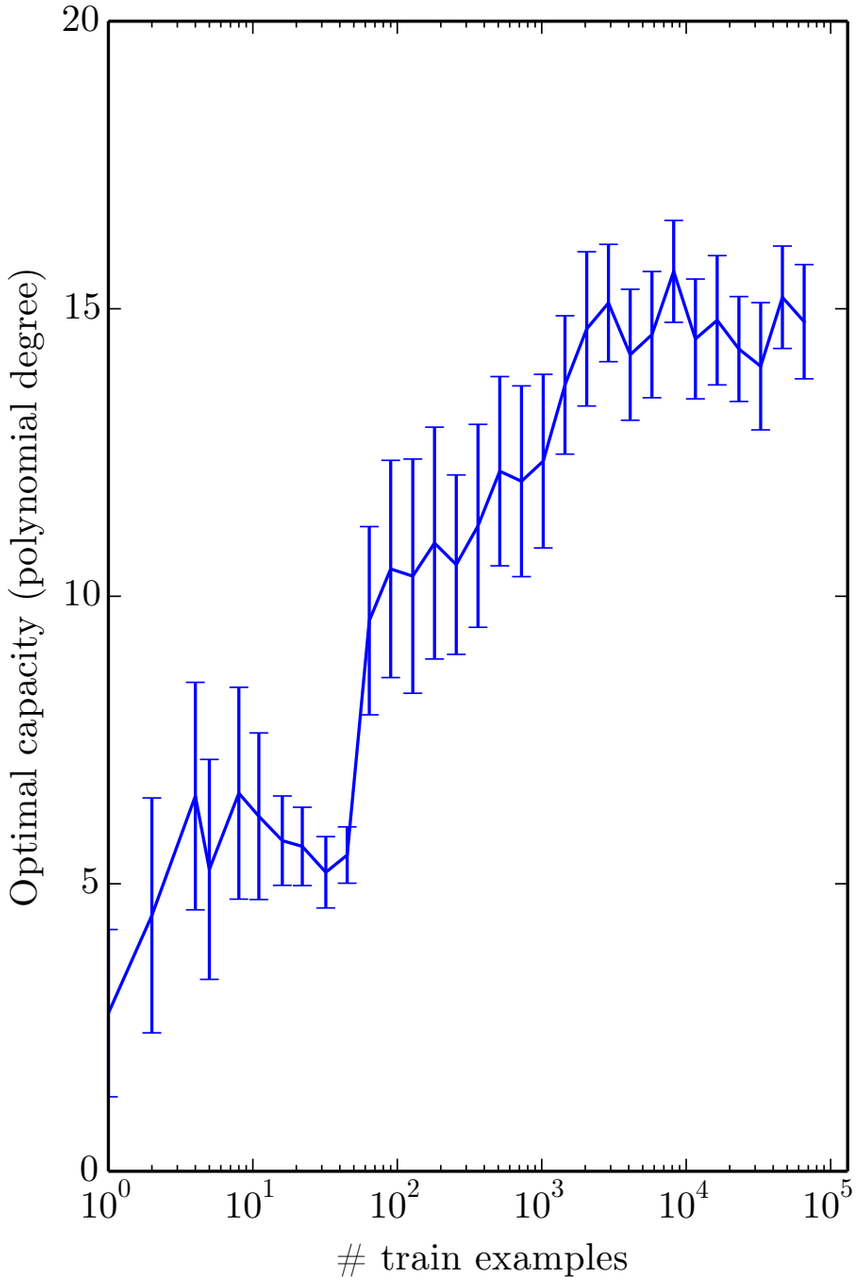


High test error

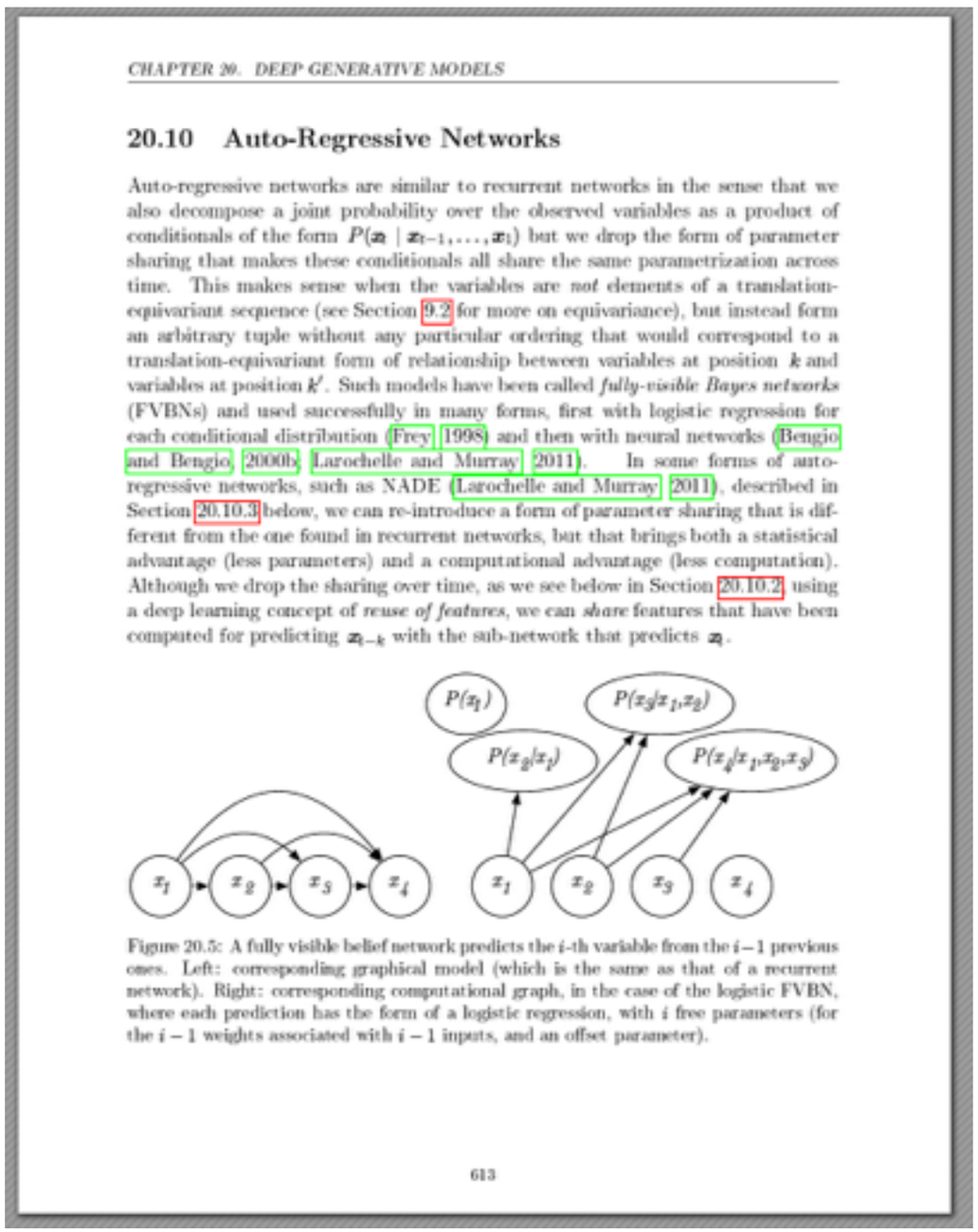
- Add dataset augmentation
- Add dropout
- Collect more data

Increasing training set size





Deep Learning textbook



CHAPTER 20. DEEP GENERATIVE MODELS

20.10 Auto-Regressive Networks

Auto-regressive networks are similar to recurrent networks in the sense that we also decompose a joint probability over the observed variables as a product of conditionals of the form $P(\boldsymbol{x}_t \mid \boldsymbol{x}_{t-1}, \ldots, \boldsymbol{x}_1)$ but we drop the form of parameter sharing that makes these conditionals all share the same parametrization across time. This makes sense when the variables are *not* elements of a translation-equivariant sequence (see Section 9.2 for more on equivariance), but instead form an arbitrary tuple without any particular ordering that would correspond to a translation-equivariant form of relationship between variables at position k and variables at position k'. Such models have been called *fully-visible Bayes networks* (FVBNs) and used successfully in many forms, first with logistic regression for each conditional distribution (Frey, 1998) and then with neural networks (Bengio and Bengio, 2000b; Larochelle and Murray, 2011). In some forms of auto-regressive networks, such as NADE (Larochelle and Murray, 2011), described in Section 20.10.3 below, we can re-introduce a form of parameter sharing that is different from the one found in recurrent networks, but that brings both a statistical advantage (less parameters) and a computational advantage (less computation). Although we drop the sharing over time, as we see below in Section 20.10.2, using a deep learning concept of *reuse of features*, we can *share* features that have been computed for predicting $\boldsymbol{x}_{t-k}$ with the sub-network that predicts $\boldsymbol{x}_t$.

Figure 20.5: A fully visible belief network predicts the i-th variable from the $i-1$ previous ones. Left: corresponding graphical model (which is the same as that of a recurrent network). Right: corresponding computational graph, in the case of the logistic FVBN, where each prediction has the form of a logistic regression, with i free parameters (for the $i-1$ weights associated with $i-1$ inputs, and an offset parameter).

613

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goodfeli.github.io/dlbook