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?

Neural nets 101
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?
Increasing depth

Effect of Depth

Test accuracy (%)

Number of hidden layers
High test error

- Add dataset augmentation
- Add dropout
- Collect more data
Increasing training set size

Error (MSE)

Bayes error
Train (quadratic)
Test (quadratic)
Test (optimal capacity)
Train (optimal capacity)

Optimal capacity (polynomial degree)
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 $P(z_t | z_{t-1}, \ldots, z_1)$ 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 29.3 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 (2008). In some forms of auto-regressive networks, such as NADE (Larochelle and Murray 2011). As 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 20.10.3, using a deep learning concept of reuse of features, we can share features that have been computed for predicting $z_{t-1}$ with the sub-network that predicts $z_t$.

Figure 20.5: A fully-visible 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).