Recent advances in model compression

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Joint work with Rich Caruana, Gregor Urban, Abdel-rahman Mohamed, Charles Sutton, Shengjie Wang, Özlem Aslan, Samira Ebrahimi Kahou, Matthai Philipose and Matthew Richardson

TFML 2017
NEURAL NETWORKS

They work amazingly well.

We are largely limited to empirical exploration.
They work amazingly well.
NEURAL NETWORKS

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- We are largely limited to empirical exploration.
THE NEURAL NETWORK ZOO

Figure from asimovinstitute.org/neural-network-zoo/.
Learnability  Representability
Learnability $\neq$ Representability
MODEL COMPRESSION (AKA KNOWLEDGE DISTILLATION)

- Idea: take predictions from a big, complex, accurate classifier (a teacher) and train a simpler model (a student) using them instead of training labels.
Model compression (aka Knowledge Distillation)

- Idea: take predictions from a big, complex, accurate classifier (a teacher) and train a simpler model (a student) using them instead of training labels.
- That is, optimise

\[
L = - \sum_j \sum_c p(c|x_j) \log q(c|x_j),
\]

where \( p(c|x_j) \) is teacher’s posterior probability of class \( c \) given \( x_j \) and \( q(c|x_j) \) is the same for the student.
MODEL COMPRESSION (AKA KNOWLEDGE DISTILLATION)

- Alternatively,

\[
L = \lambda \left[ -\sum_j \sum_c p(c|x_j) \log q(c|x_j) \right] + (1-\lambda) \left[ -\sum_j \log q(y_j|x_j) \right],
\]

where \( p(c|x_j) \) is teacher’s posterior probability of class \( c \) given \( x_j \) and \( q(c|x_j) \) is the same for the student.
MODEL COMPRESSION

Why does that work?
MODEL COMPRESSION

Why does that work?

Hypotheses:
Why does that work?

Hypotheses:
- Each example shown to the student model is given with a richer supervision signal.
MODEL COMPRESSION

Why does that work?

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- Each example shown to the student model is given with a richer supervision signal.
- Cleans noisy labels.
Why does that work?

Hypotheses:
- Each example shown to the student model is given with a richer supervision signal.
- Cleans noisy labels.
- A way to transfer an inductive bias between models.
MODEL COMPRESSION

- Large ensemble $\rightarrow$ single non-convolutional net (Bucila et al., 2006).
MODEL COMPRESSION

- Large ensemble $\rightarrow$ single non-convolutional net (Bucila et al., 2006).
- Ensemble of deep convolutional nets $\rightarrow$ single shallow non-convolutional net (Ba and Caruana, 2014).
Do deep nets really need to be deep?

Figure from Ba and Caruana (2014).
Model compression

- Large ensemble → single non-convolutional net (Bucila et al., 2006).
- Ensemble of deep convolutional nets → single shallow non-convolutional net (Ba and Caruana, 2014).
- Ensemble of deep non-convolutional nets → single deep non-convolutional net (Hinton et al., 2014).
MODEL COMPRESSION

- Large ensemble $\rightarrow$ single non-convolutional net (Bucila et al., 2006).
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- Ensemble of very deep convolutional nets $\rightarrow$ single shallow convolutional net (Urban et al., 2016).
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- Ensemble of very deep convolutional nets $\rightarrow$ single shallow convolutional net (Urban et al., 2016).
- Ensemble of deep recurrent nets $\rightarrow$ single deep convolutional net (Geras et al., 2016).
Do deep convolutional nets really need to be deep (or even convolutional)?

- We know that fully connected nets are compressible.
Do deep convolutional nets really need to be deep (or even convolutional)?

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- **Question 1.** Can we compress deep convolutional networks into shallow convolutional networks?
Do deep convolutional nets really need to be deep (or even convolutional)?

- We know that fully connected nets are compressible.
- **Question 1.** Can we compress deep convolutional networks into shallow convolutional networks?
- **Question 2.** Can we compress deep convolutional networks into fully connected networks?
CIFAR-10 data set

- Labelled subset of the Tiny 80M images data set.
- 60k 32x32 RGB images.
- 10 classes: airplane, automobile, bird, cat, deer, dog, frog, horse, sheep, truck.
- Each class contains 6k images.
Training the Teacher and the Students

- The teacher: 8 convolutional layers and 2 fully connected layers.
TRAINING THE TEACHER AND THE STUDENTS

- The teacher: 8 convolutional layers and 2 fully connected layers.
- Various possible student architectures.
Training the Teacher and the Students

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- Various possible student architectures.
- We need to be extremely careful.
Training the Teacher and the Students

▶ The teacher: 8 convolutional layers and 2 fully connected layers.
▶ Various possible student architectures.
▶ We need to be extremely careful.
▶ We use Bayesian optimisation to find the best hyperparameters.
Deep convolutional nets really need to be deep.
Deep convolutional nets really need to be deep. And convolutional.
Deep convolutional nets really need to be deep. And convolutional. But perhaps not that deep.
Speech recognition $\approx$ object recognition
Speech recognition framework:

Speech recognition $\approx$ object recognition
Speech recognition framework:
  ▶ Sample many windows of speech. Train a classifier.
Speech recognition framework:

- Sample many windows of speech. Train a classifier.
- Use decoding to get words.
The Switchboard Data Set

- A benchmark for speech recognition.
THE SWITCHBOARD DATA SET

- A benchmark for speech recognition.
- Very large, 309 hours of speech, 18 GB.
The Switchboard Data Set

- A benchmark for speech recognition.
- Very large, 309 hours of speech, 18 GB.
- We sample training examples of size $31 \times 41$, 9000 output classes.
**CNNs for Speech**

<table>
<thead>
<tr>
<th>Layer Type</th>
<th>Size</th>
</tr>
</thead>
<tbody>
<tr>
<td>softmax</td>
<td></td>
</tr>
<tr>
<td>fully connected, 2048</td>
<td></td>
</tr>
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</tr>
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</tr>
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</tr>
<tr>
<td>convolution, 7×7, 324</td>
<td></td>
</tr>
<tr>
<td>max pooling, 3×1</td>
<td></td>
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<td>input (31x41)</td>
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<td>3×3, 192</td>
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<td>3×3, 96</td>
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**Sainath et al.-style CNN**

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CNNs vs LSTMS on the Switchboard data set

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CNNs vs LSTMs for speech

Figure from deeplearning.net

Figure from Graves et al. (2013)
Can we do better?

- Different network structures $\rightarrow$ different inductive biases.
Can we do better?

- Different network structures → different inductive biases.
- Can we have two models in one?
Can we do better?

- Different network structures $\rightarrow$ different inductive biases.
- Can we have two models in one?
- Yes, there is an easy way to do this - ensembling.
Ensembling

\[ p(y|x_i) = \gamma p_{\text{LSTM}}(y|x_i) + (1 - \gamma)p_{\text{CNN}}(y|x_i) \]
ENSEMBLING

\[ p(y|x_i) = \gamma p_{\text{LSTM}}(y|x_i) + (1 - \gamma)p_{\text{CNN}}(y|x_i) \]
ENSEMBLING

\[ p(y|x_i) = \gamma p_{\text{LSTM}}(y|x_i) + (1 - \gamma)p_{\text{CNN}}(y|x_i) \]

**Big issue:** LSTM is 6 times slower than the CNN. We need to have two models in one CNN.
HOW TO DO COMPRESSION WITH SWITCHBOARD

- Very large data set, 309 hours of speech, 18 GB.
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- Very large data set, 309 hours of speech, 18 GB.
- $31 \times 41$ inputs, 9000 output classes.
HOW TO DO COMPRESSION WITH SWITCHBOARD

- Very large data set, 309 hours of speech, 18 GB.
- $31 \times 41$ inputs, 9000 output classes. $\Rightarrow$ Predictions would take 3.6 TB.
HOW TO DO COMPRESSION WITH SWITCHBOARD

\[
M(C) = \frac{1}{|\{x_i\}|} \sum_{x_i} \sum_{y \in \text{TOP}_C(x_i)} p(y|x_i).
\]
How to do compression with Switchboard

\[ M(C) = \frac{1}{|\{x_i\}|} \sum_{x_i} \sum_{y \in \text{TOP}_C(x_i)} p(y|x_i). \]

We only keep predictions for classes covering 99% probability mass, we truncate after 90 classes.
Blending LSTMs into CNNs

\[ L(\lambda) = \lambda \left[ - \sum_{j} \sum_{c} p(c|x_j) \log q(c|x_j) \right] + (1 - \lambda) \left[ - \sum_{j} \log q(y_j|x_j) \right] \]
BLENDING LSTMs INTO CNNs

\[ L(\lambda) = \lambda \left( -\sum_{j} \sum_{c} p(c|x_j) \log q(c|x_j) \right) + (1-\lambda) \left( -\sum_{j} \log q(y_j|x_j) \right) \]
## Results

<table>
<thead>
<tr>
<th>Model Type</th>
<th>FER</th>
<th>WER</th>
<th>Model Size</th>
<th>Execution Time</th>
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<tr>
<td>Sainath et al.-style CNN</td>
<td>37.93%</td>
<td>15.5</td>
<td>≈ 75M</td>
<td>× 0.75</td>
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<tr>
<td>vision-style CNN</td>
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<td>14.1</td>
<td>≈ 75M</td>
<td>× 1.0</td>
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<td>34.15%</td>
<td>14.4</td>
<td>≈ 65M</td>
<td>× 5.8</td>
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<tr>
<td>LSTM → CNN blending</td>
<td>34.11%</td>
<td>13.83</td>
<td>≈ 75M</td>
<td>× 1.0</td>
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SUMMARY OF MODEL BLENDING

Speech recognition can be improved a lot by vision-style CNNs.

RNNs and CNNs learn different aspects of the data.

Recurrent networks for speech recognition may not need to be recurrent.

Only “dim knowledge” necessary.
SUMMARY OF MODEL BLENDING

- Speech recognition can be improved a lot by vision-style CNNs.
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- Speech recognition can be improved a lot by vision-style CNNs.
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- RNNs and CNNs learn different aspects of the data.
- Recurrent networks for speech recognition may not need to be recurrent.
- Only “dim knowledge” necessary.
SELF-COMPRESSION

- Train model A.

- Train an identical model B, mimicking model A with $\lambda = 0.5$.

- Model B is more accurate than model A in FER!
  - FER: 35.51 → 34.61
  - WER: 14.1 → 14.1
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- Model B is more accurate than model A in FER!
  - FER: 35.51 $\rightarrow$ 34.61.
Thank you!

Do Deep Convolutional Nets Really Need to be Deep (Or Even Convolutional)? ICLR 2017
Gregor Urban, Krzysztof J. Geras, Samira Ebrahimi Kahou, Ozlem Aslan, Shengjie Wang, Rich Caruana,
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Blending LSTMs into CNNs. ICLR 2016
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