COMS0018: PRACTICAL-Lab4

Dima Damen
Dima.Damen@bristol.ac.uk

Bristol University, Department of Computer Science
Bristol BS8 1UB, UK

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What else can we do?

- Data Augmentation
- Debugging Strategies
- Dropout

Data Augmentation

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  - **More importantly...** to accommodate invariances

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Number plate recognition	translation, scaling
Action Recognition	translation, rotation, scaling, viewpoint, speed

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  - Viewpoint: Minor - affine transformations, otherwise :-(collect more data!

Invariances in data

- Other invariances:
  - invariance to random noise
  - invariance to occlusion
  - invariance to lighting conditions
  - invariance to time of year!? — Generative!

Data Augmentation

- Data augmentation for invariances existed before deep learning

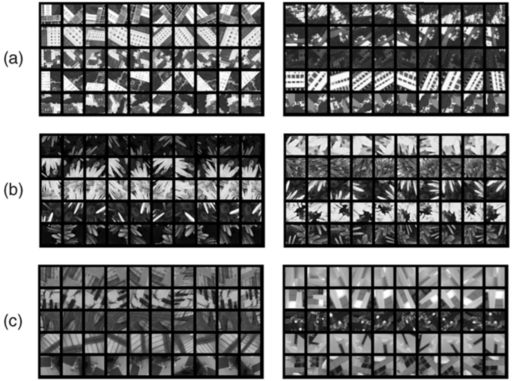

Fig. 7. Warped patches from the images of Fig. 6 show the range of

Ozuysal et al (2010). Fast Keypoint Recognition Using Random Ferns. TPAMI.

Data Augmentation

- Why can't current deep learning methods do that automatically for us?

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  - $\rightarrow$ fix and start over

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- When a general machine learning code performs poorly, including deep learning code, it is very tricky to decide whether that is a bug in the code or a problem in the algorithm
- Compiling correctly and getting numbers out is not an indication of correctness
- We do not know what the "correct" implementation will give in terms of accuracy, that is in fact what we wish to discover
- Careful debugging is thus a must

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- For a classifier with unbalanced classes??

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- Monitor the model in action
- Look at failure cases (qualitative assessment)
- Checkpoints and model saving

Debugging Strategies

"Directly observing the machine learning model performing its task will help to determine whether the quantitative performance numbers it achieves seem reasonable"

Goodfellow et al, p432

Debugging Strategies

"Evaluation bugs can be some of the most devastating bugs because they can mislead you into believing your system is performing well when it is not"

Goodfellow et al, p432

Dropout

- What is regularisation?
- Remind yourself about dropout, as a regularisation/ensemble approach, from the lectures.

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- Implement and evaluate a variety of data augmentation techniques
- Implement dropout as one of the most common regularisation approaches

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- Labs should be individual work. You can use your code (any or all the group members) to start your project.

And now....

READY....

STEADY....

GO...