COMSM0045: PRACTICAL-Lab4

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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 colour variations
  - invariance to time of year!? — Generative!

Data Augmentation

- Data augmentation for invariances existed before deep learning

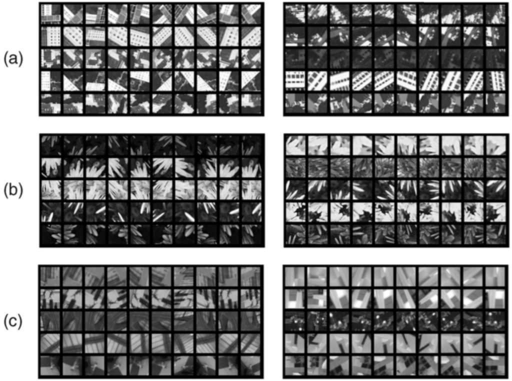

Fig. 7. Warped patches from the images of Fig. 6 show the range of

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?

Data Augmentation

- Crazier ideas are starting to show up in data augmentation... For example, methods newly use Mixup

[1]

[1] Fig from https://amitness.com/2020/05/data-augmentation-for-nlp/

Data Augmentation

- Or CutMix

[2]

[2] Fig from Yun et al (2019). CutMix: Regularization Strategy to Train Strong Classifiers with Localizable Features

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  - $\rightarrow$ fix and start over

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- 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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- 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

And now....

READY....

STEADY....

GO...