Transfer Notes

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1 Extra literature

2 Paper litreview section commented out below

3 Appendix: Notes and comments

Structure help

A literature review should be structured like any other essay: it should have an introduction, a middle or main body, and a conclusion.

Introduction Might be worth starting from the key papers: Independent components of natural scenes are edge filters, and

The introduction should:

– define your topic and provide an appropriate context for reviewing the literature;
  My answer here [from research proposal]
– establish your reasons i.e. point of view for reviewing the literature; Identify and progress current state-of-art signal detection by making use of and learning from recent deep learning, (reinforcement learning and control theory) progress. Or: Identify and unify specific quality research in specific fields for the creation of a robust general purpose detector. Bring automation, a step closer to intelligence, to the detection framework to remove the human-in-the-loop element that is frequently present when designing detectors.
– explain the organisation i.e. sequence of the review; state the scope of the review i.e. what is included and what isnt included. For example, if you were reviewing the literature on obesity in

children you might say something like: There are a large number of studies of obesity trends in the general population. However, since the focus of this research is on obesity in children, these will not be reviewed in detail and will only be referred to as appropriate.

Main body The middle or main body should:

- organise the literature according to common themes;
  - Traditional approaches to Acoustic Event Detection
  - Deep Learning:
    - LSTMs
    - Other NNs
    - CNNs
      - Spectrogram data
      - Raw/combined/other
- provide insight into the relation between your chosen topic and the wider subject area e.g. between obesity in children and obesity in general;

  .. answer
- move from a general, wider view of the literature being reviewed to the specific focus of your research. General wide view: signal detection options, historical uses of techniques. More specific: deep learning advances, Bayesian involvement/improvements, focus on integrating best approaches. Most specific: More theoretical approach to choosing weights with information-theoretic criteria

Conclusion The conclusion should:

- summarise the important aspects of the existing body of literature;
- evaluate the current state of the literature reviewed;
- identify significant flaws or gaps in existing knowledge;
- outline areas for future study;
- link your research to existing knowledge.

Other helpful material found here: Toronto Eng Lit Review Guidance

3.1 Comments from Steve

- Harmonic detection
- Detecting weak signals embedded in noise
- Structure in time series
- HMMs? More complex alternative to traditional HMMs: LSTMs?
- CNNs, Deep Learning? Critical? Failings? How do we address those?
- CNN: static. Hybrid LSTM-CNNs. Optimising architecture? Agile automated way of adapting model structure: growing to be more complex to keep solving problem or shrink when it is easier?
- Fusing with probabilistic reasoning: deep kernel methods: major methodological challenge
- Data-analytic side of the HumBug: spatio-temporal distributions: working dynamically with real data from sensors on field
- State of the art?
- What models are out there?
- Are there alternate approaches for discovering weak signals in noise that are not based on neural networks?
- Increasing work on seeing CNNs as deep kernel learning methods?
- Convolutional GPs?
- Recurrent GPs as replacement to LSTMs?

4 Hitlist of 3 things to really do/address: by next week: for work on coming year.

1. Hypothesise that wavelet does better than STFT in data-scare scenario. Test, and if true, focus on improving computational efficiency of wavelet algorithm or replace with DWT. Does DWT loss of information degrade performance on a) our data and b) other applications due to poor generalisability (as was found to be the case with MFCC/related transforms in speech recognition applications)?
2. Investigate neural network/Bayesian hybrid approaches for more principled uncertainty handling and model learning. Deep kernel methods (CNN/DKL joint parameter inference) have been supposedly shown to significantly improve performance over regular GPs, GPs on the outer layer of a DNN, and marginally surpassed performance of an equivalent standalone CNN on MNIST data, as well as in a

multitude of regression tasks. Apply to our tried and tested dataset (code is available, although not trivial to implement)

3. Novelty measure with neural networks: how confident is network about predictions made on new data? Perhaps gateway work before entering deep kernel methods/more principled methods of uncertainty propagation

1. Bit for bit: best least squares reconstruction? Worth investigating. Overlapping redundancy helps. Is there something we can learn from the way wavelets form a representation that we can bring into the frontend into a new breed of network. We have conditioning on wavelet, then CNN, not a fully end-to-end in wavelets. Learn wavelet basis with nets. Frequency transform kernel.
2. Bayes opt to jump between proposed model structures. Builds up to points of evidence in a value space, where you don't need to try absolutely everything because you believe the value has some local smoothness. E.g. model structures not too different will work similarly well. Extended to CNN/GP hybrids? Principle to evolutionary computing (more modern) to address this methodology? The automated statistician: brute force approach. ABCD
3. Extension of raiders of the lost architecture to hybrid networks:
4. Bringing in doppler, traditional sigproc stuff : LSTMs? Dataset has more pitch shifts in it
5. Context of how we make models in general
6. Data may be archived as unusual -¿ go to crowdsourcing. Increasing knowledge of coverage of algorithm around it. ”Lifelong learning”: adapting over time. Feedback mechanism for uncertain results.
7. LSTMs: important, hybrid CNN/LSTM Fusing with probabilistic reasoning: find current state-of-art: really address potential further research points, but also caveats of papers (identify dead ends maybe?) - addresses Steve's comment about seeing CNN as a deep kernel learning method

New dataset? Synthetic augmentation. Generate probabilistically. GANs/fGANs. Scaffold model. Hallucinate data.

Other points:

– Hypothesise that wavelet does better in data-scarce scenario: test
– If true, important to focus on improving wavelet algorithm for computational efficiency/replace with DWT? Is loss of information worth it?

- Novelty measure: how confident is network about predictions made on new data?
- Bring probabilistic reasoning into decision-making
- Really want to try deep kernel method e.g. Deep GP on dataset