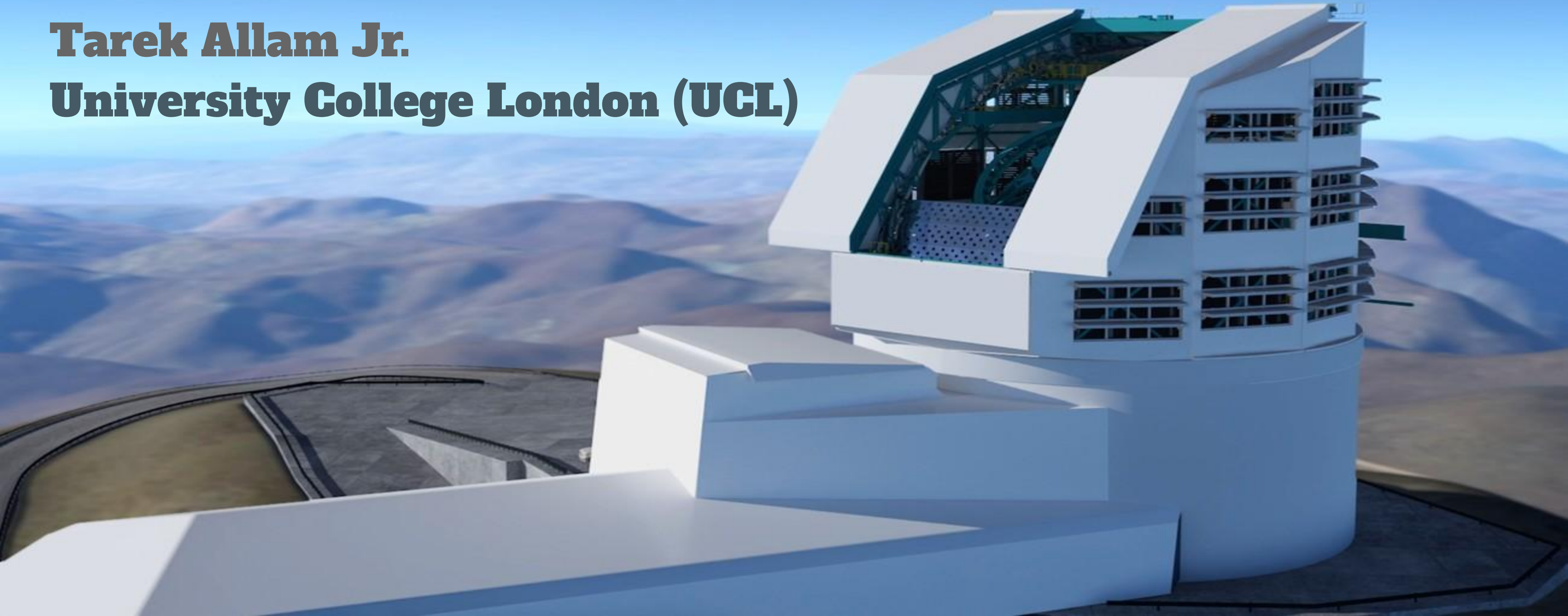
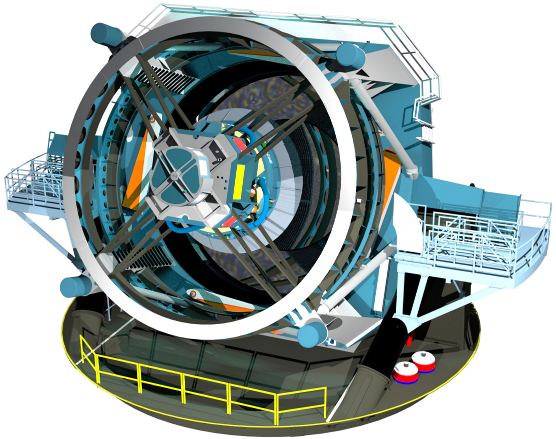
Low-latency High-throughput Classification using Deep Model Compression

Tarek Allam Jr.
University College London (UCL)

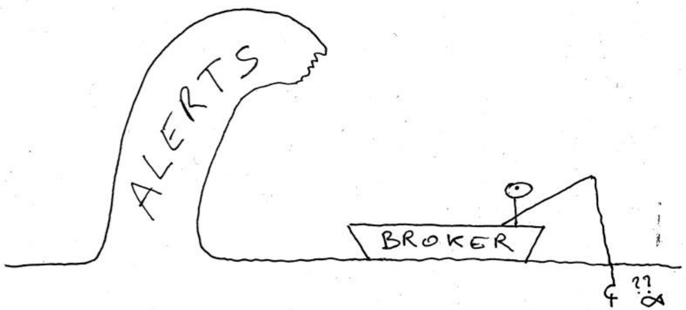


Motivation: A Deluge of Data



Overview

- 10 million alerts, per night!
- Machine Learning methods are now critical
- Accurate and fast classification required for follow up
- Desire for fast re-training of models



Peloton et al. 2020

Deep Learning to the Rescue!?

The death of feature engineering?

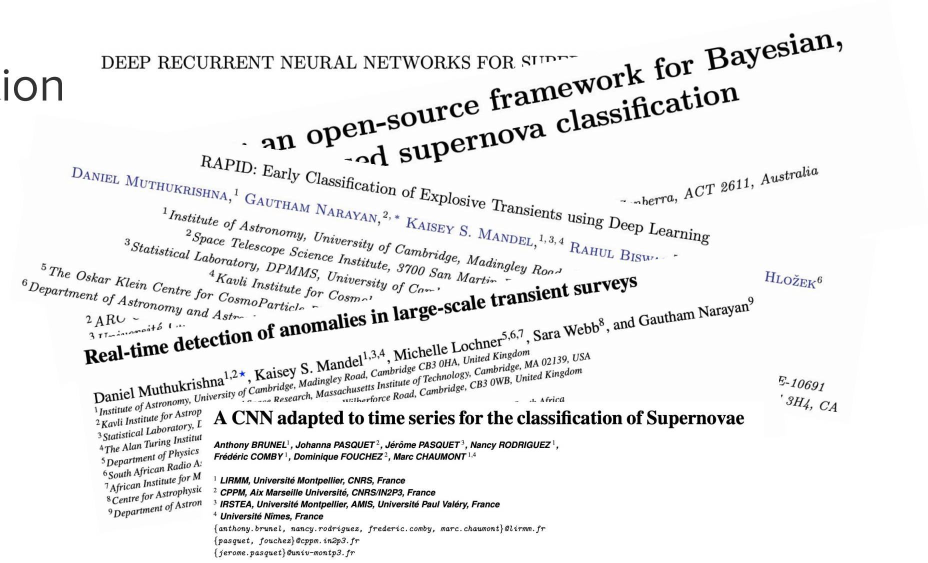
- Exploiting inherent time-series information

RNNs (inc. SuperNNova, RAPID)

CNNs (inc. TCN)

Transformers (inc. t2)

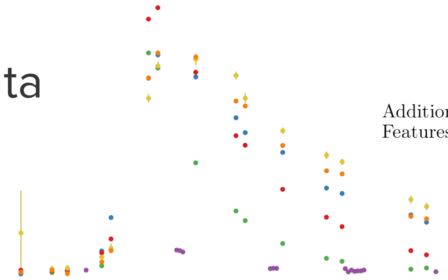
...

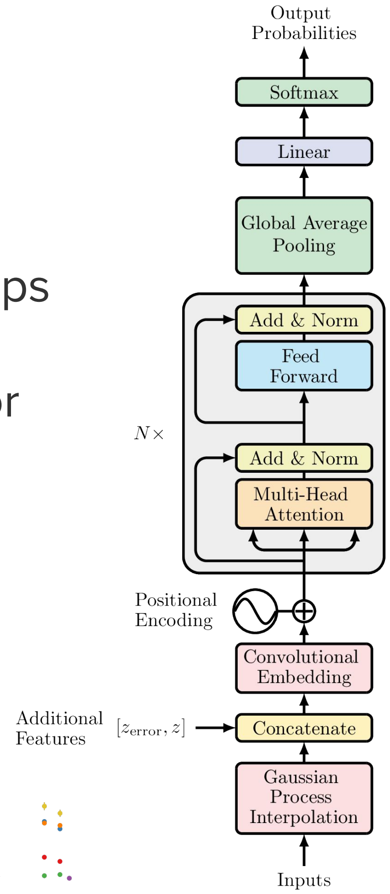


The Time-Series Transformer [t2]

Encoder++

- *Global Average Pooling* to allow for Class Activation Maps
- *Convolutional Embedding* maps time-series into a vector space
- *Concatenate* additional features
- *GP Interpolation* to handle irregular data

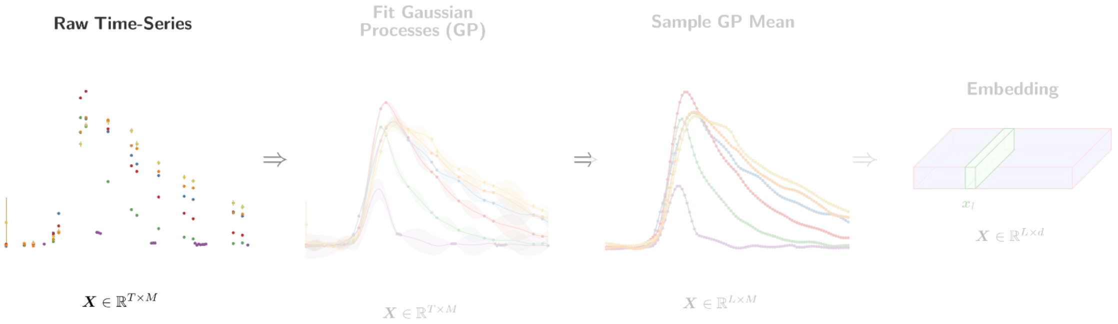


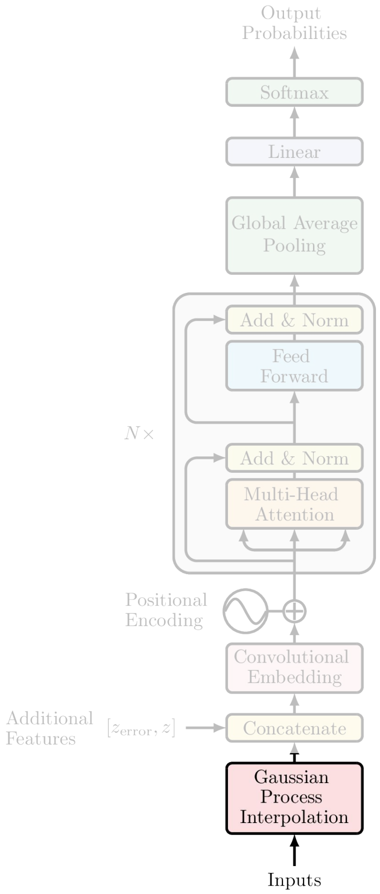


ML Pipeline

Gaussian Process Interpolation

- 2D-Matern kernel for Gaussian Process interpolation
- Evaluate at regular period, 100 points in our case





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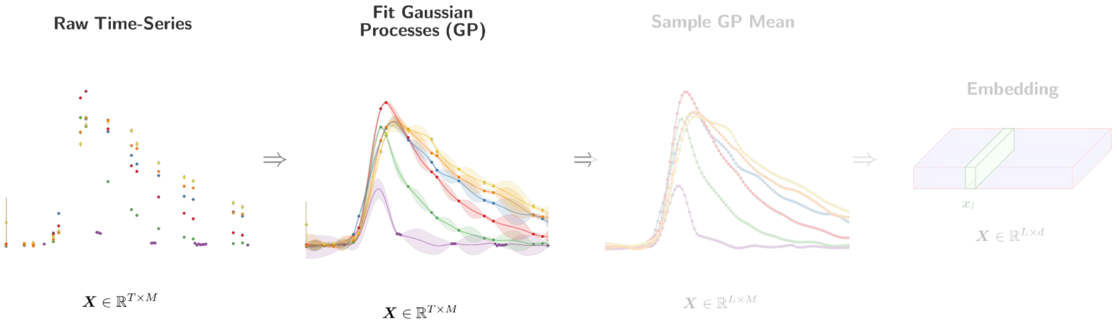

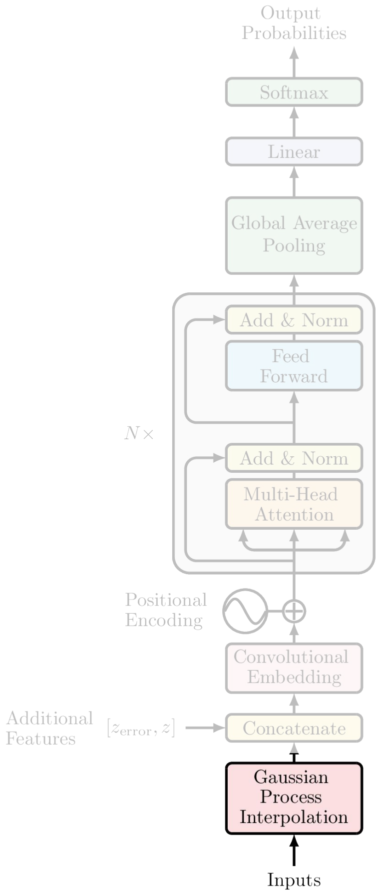

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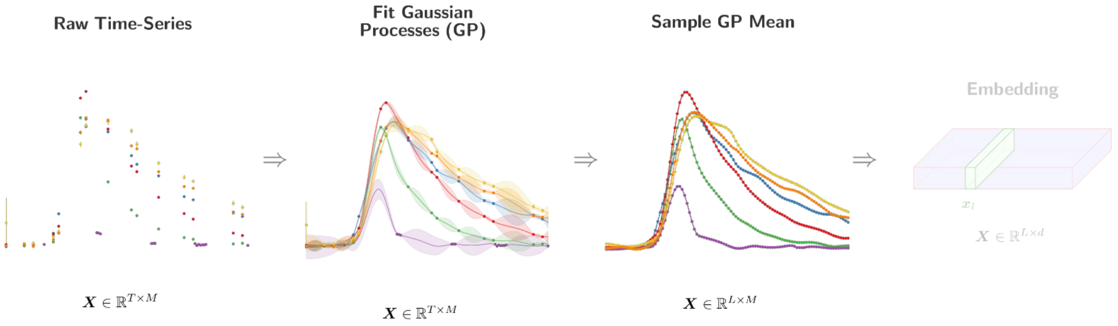

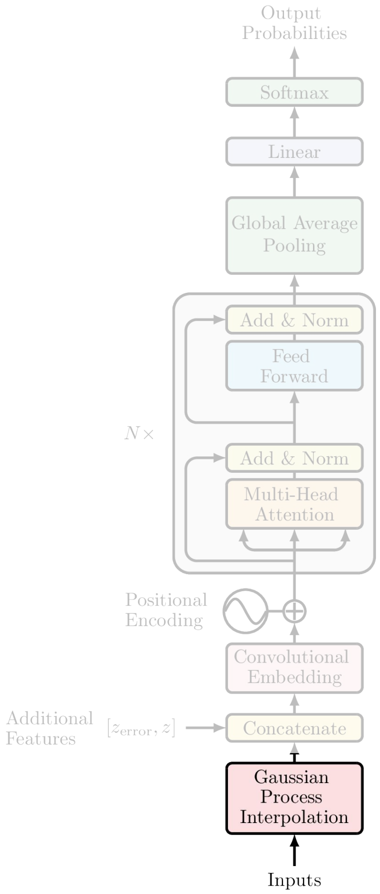

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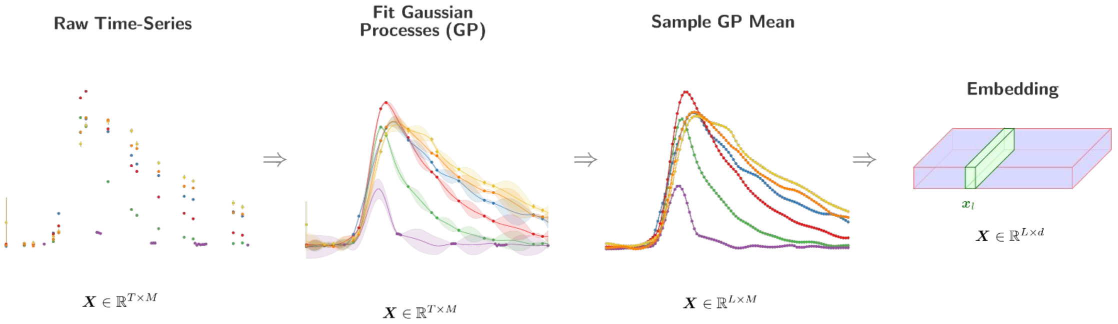

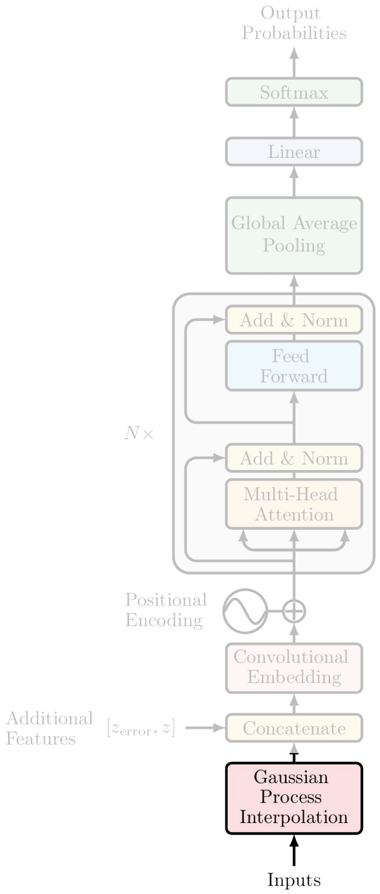

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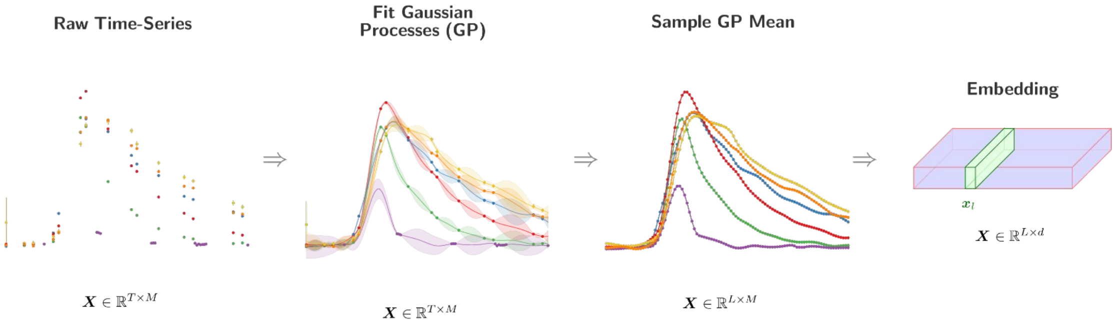
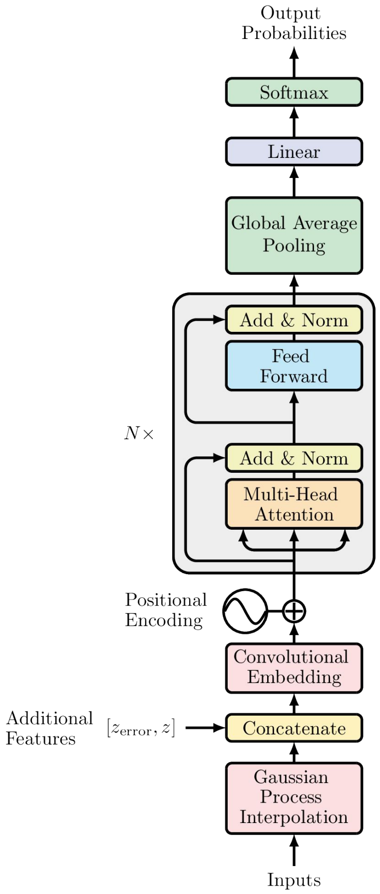
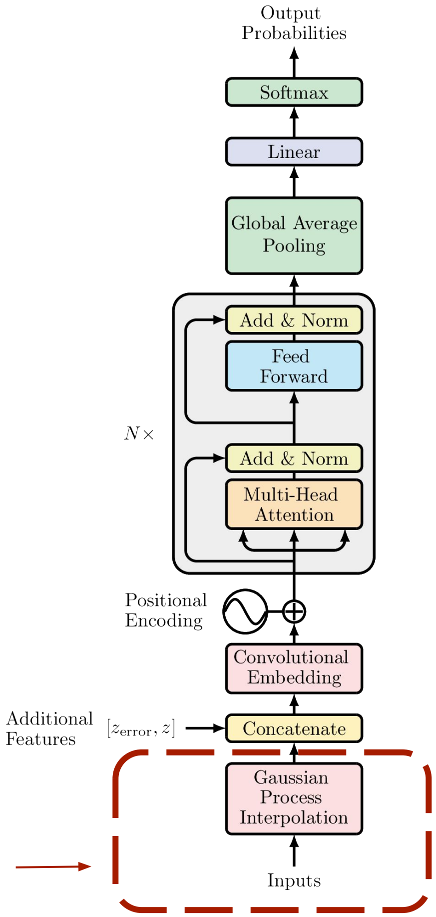
Deep Learning Magic ...





Understanding Bottlenecks



`fit_gps(raw_alert)` →

Understanding Bottlenecks

`model.predict(processed_alert)` →

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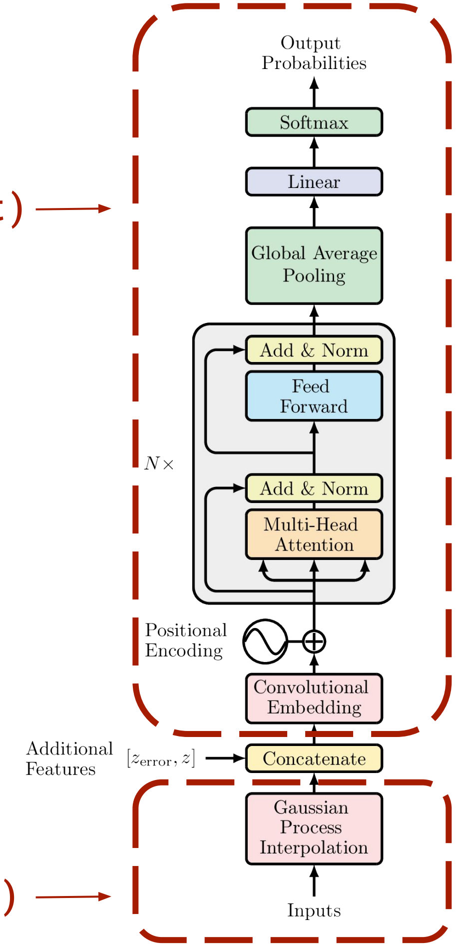

Understanding Bottlenecks

```
Total time: 5.85664 s
File: get_models.py
Function: get_model at line 29

Total time: 1.47076 s
File: ztf-load-run-lpa.py
Function: t2_probs at line 55

Line #    Hits        Time Per Hit \% Time Line Contents
==============================================================
...
206       16      139.6    8.7     9.5     df_gp_mean = generate_gp_all_objects()
...
...
...
...
...
212        8      180.8   22.6    12.3     X = df_gp_mean[cols]
213        8       12.3    1.5     0.8     X = rs(X)
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217        8     1101.7  137.7    74.9     y_preds = model.predict(X)
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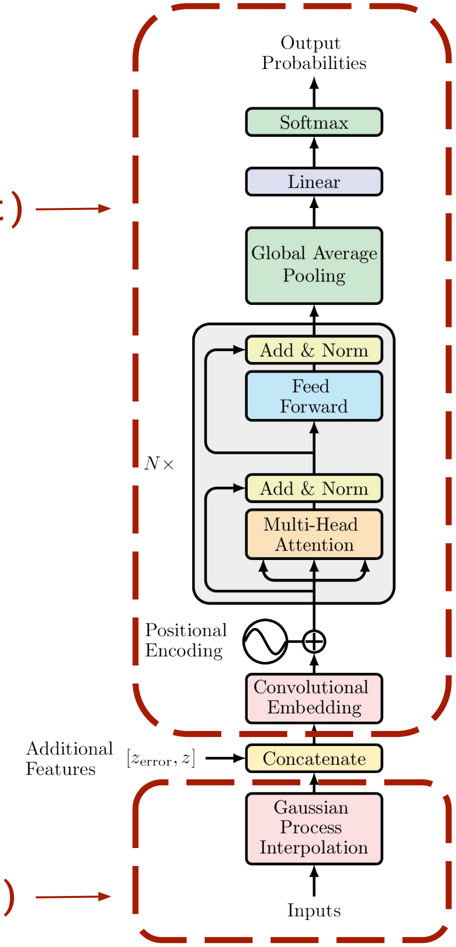

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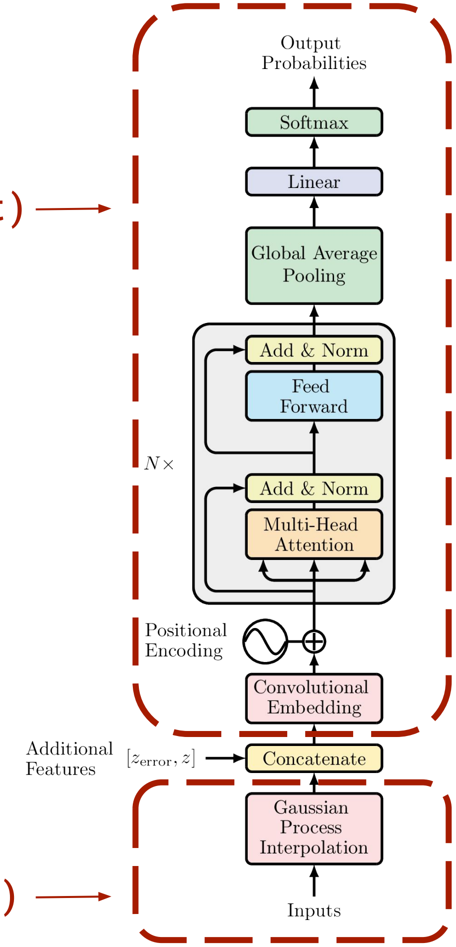

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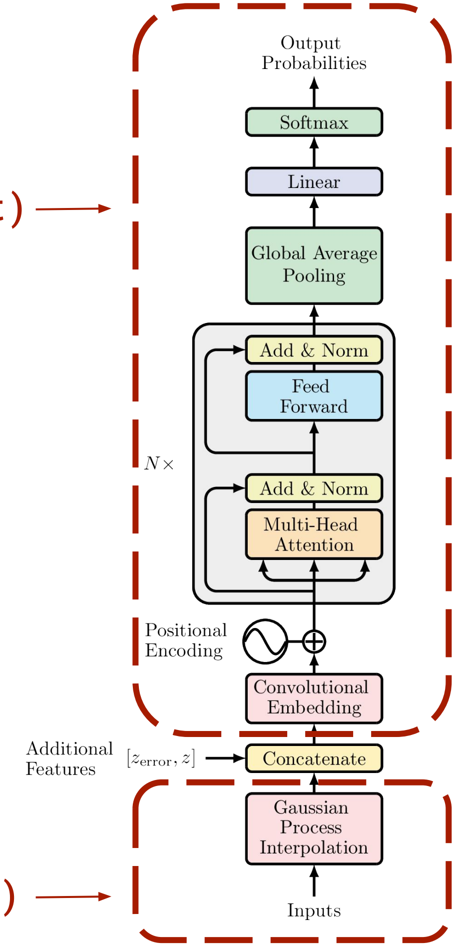


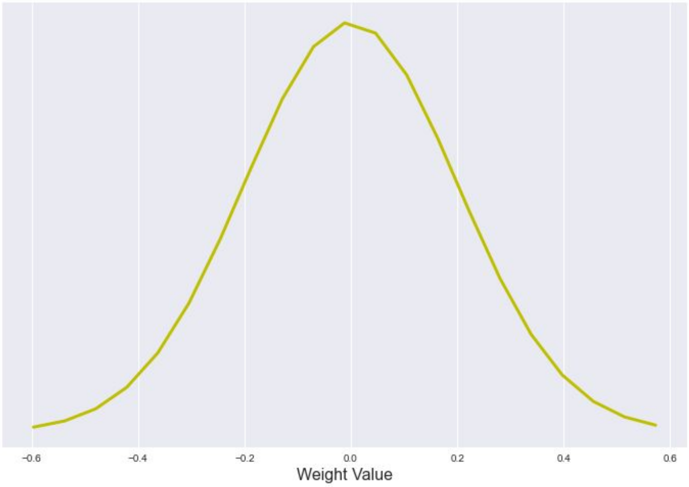
Deep Model Compression: An *Almost* Free Lunch

- Standout paper: Han et al. 2015: *Deep Compression*
    - Clustering
    - Pruning
    - Quantization
- Lossy process – expect some loss in accuracy (but improved compute and storage costs!)

Deep Model Compression: Clustering

Weight Clustering

- Reduce number of unique weights with shared weight values
- Can then leverage Huffman encoding
- Note: best to avoid clustering early layers!



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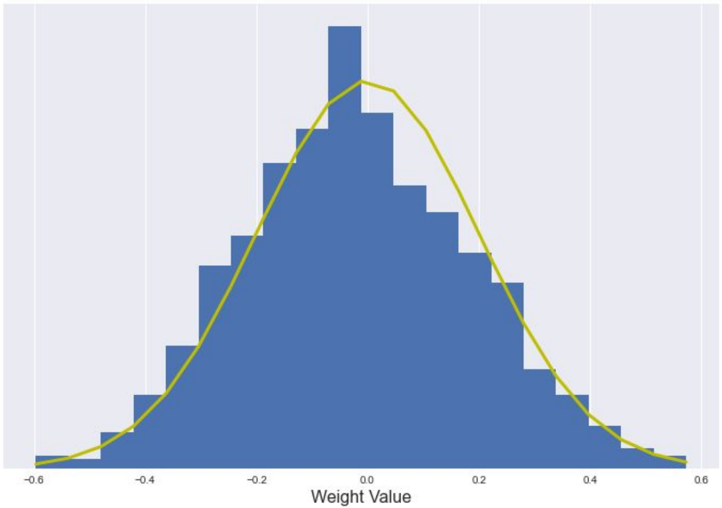
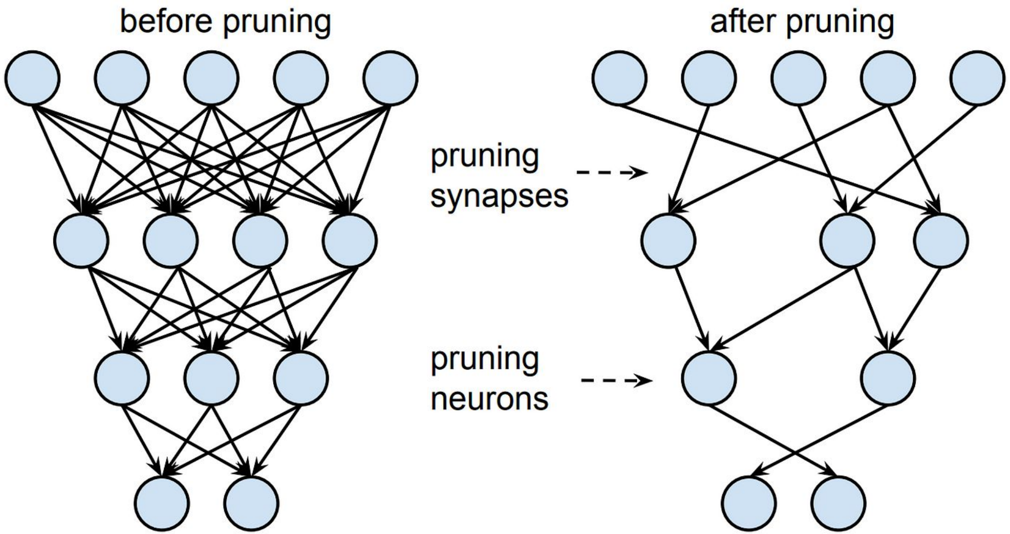


Deep Model Compression: Pruning

Weight Pruning

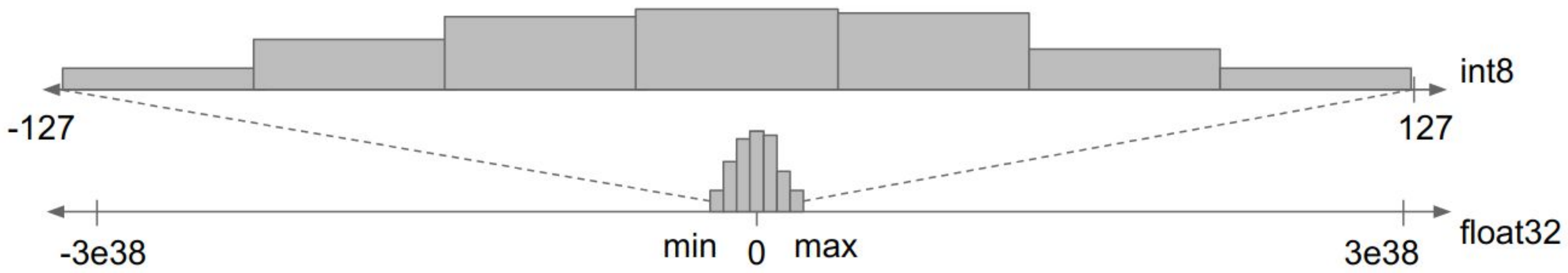
- Set low magnitude weights to zero
- Can then leverage Huffman encoding (again)
- Done *during* training



Deep Model Compression: Quantization

Weight Quantization

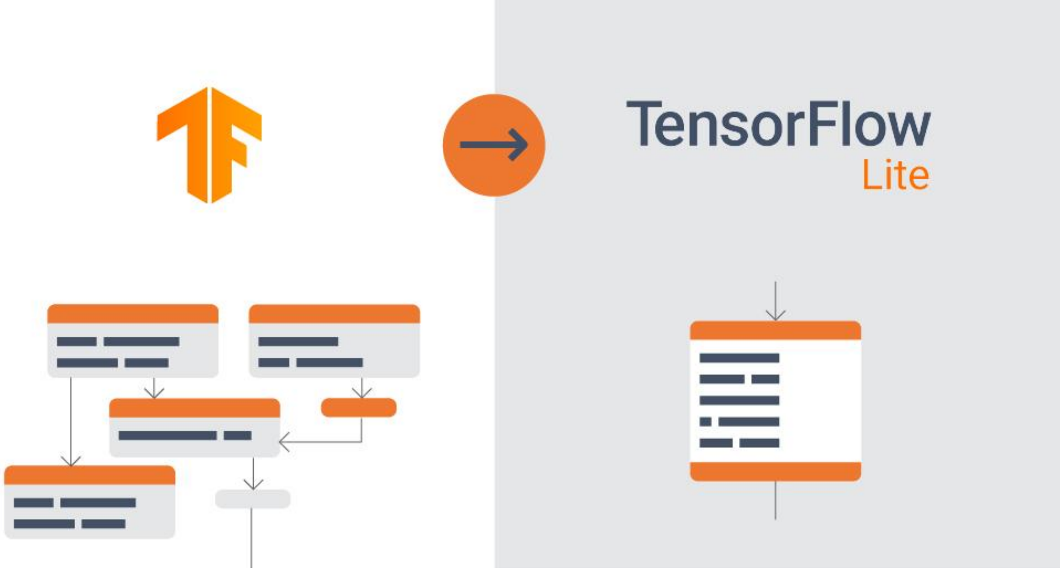
- Reduce precision of stored weight values
- Computations are still done at `float32`

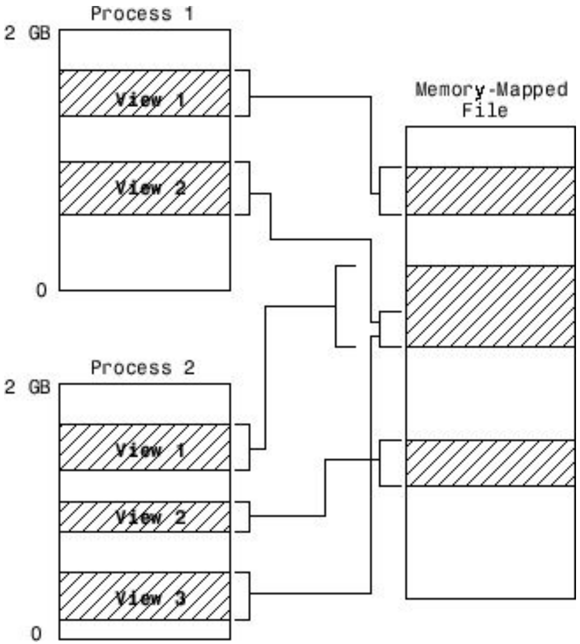


Efficient Frameworks & File Formats

From TensorFlow to TensorFlow-Lite

- Operator Fusion
- `ProtocolBuffers → FlatBuffers`





Local Tests

Compression Method	Model Size (kb)	Load Latency (s^{-3})	Inference Latency (s)	Loss
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- **18 x** reduction in model size
- **24,000 x** load time improvement
- **8 x** inference latency improvement

Production Results

- One full night of ZTF alerts ~ 200K

- Require at least 2 points on light curve

- Averaged over 20 processing runs

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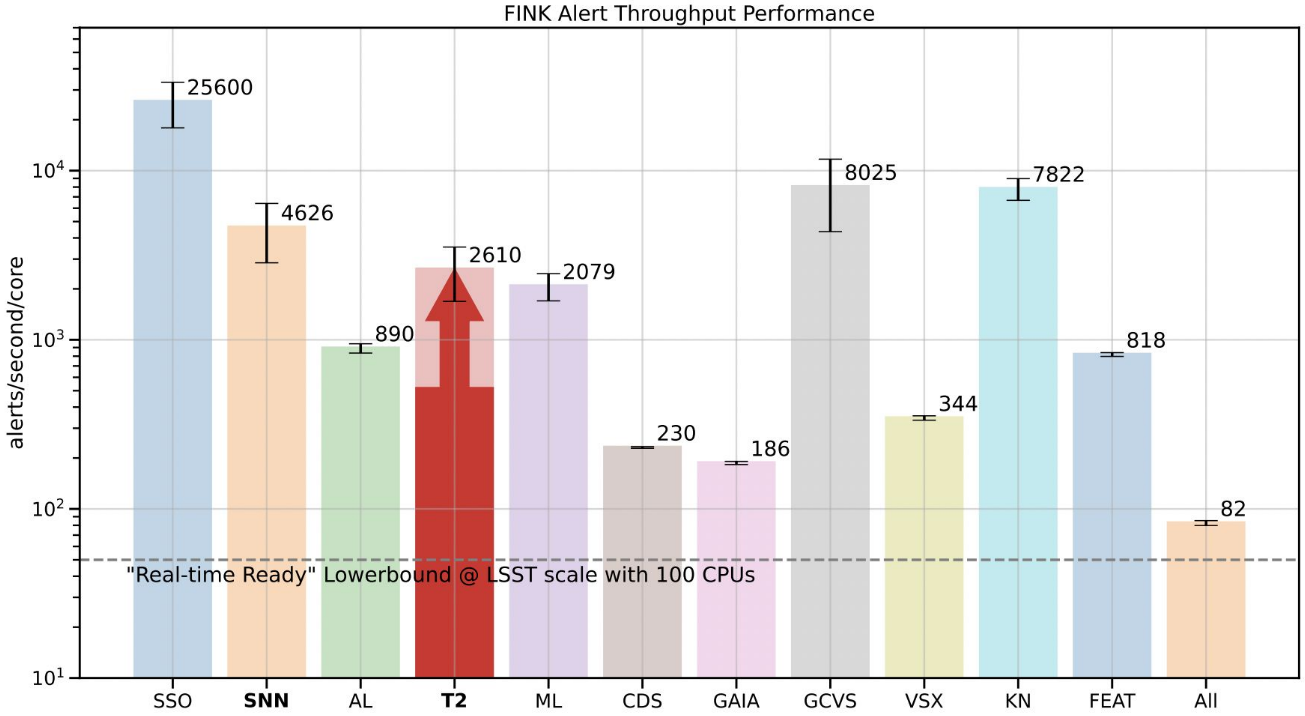
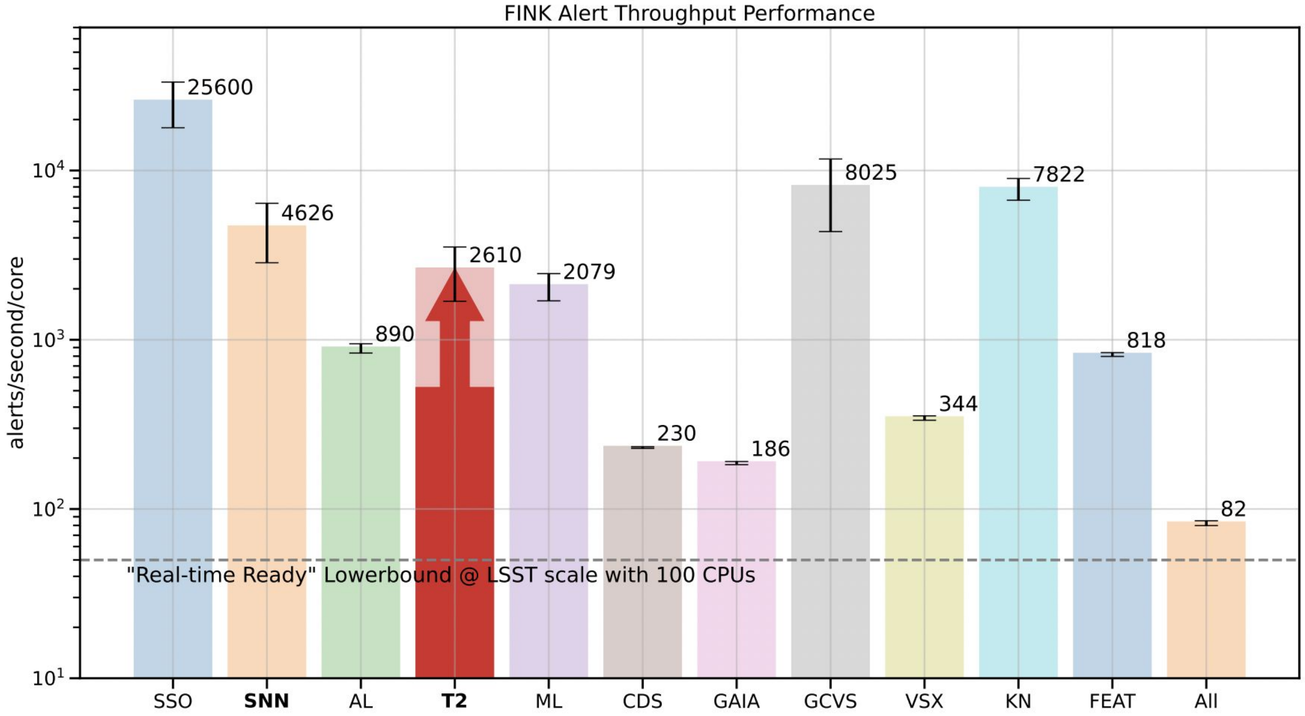
- Averaged over 20 processing runs
- **5x** throughput



Takeaways...

- Use of deep compression can be your friend, *but be careful*

- Use FlatBuffers where possible



Questions?