The Aerospace Corporation
Civil Systems Group (CSG)

Near Earth Object Detection Using Artificial Intelligence

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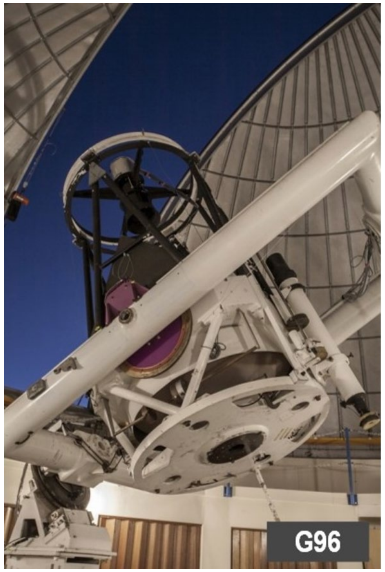
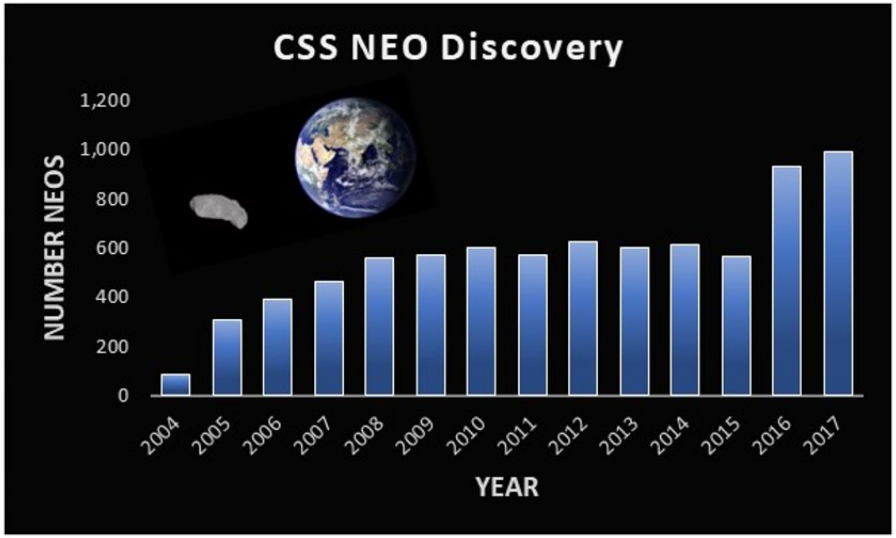
- NASA funds CSS to identify Earth-crossing asteroids > 140 meters in size
- CSS uses three telescopes in the Santa Catalina Mountains near Tucson, Arizona
  - G96: 1.5-m survey 10,560 x 10,560 pixel CCD detector
  - 703: 0.7-m survey 10,560 x 10,560 pixel CCD detector
  - I52: 1.0-m follow-up 2000 x 2000 pixel CCD detector
- CSS uses an automated process to rank order NEO candidates
- **Still requires human observers to review thousands of false positives for each NEO found**

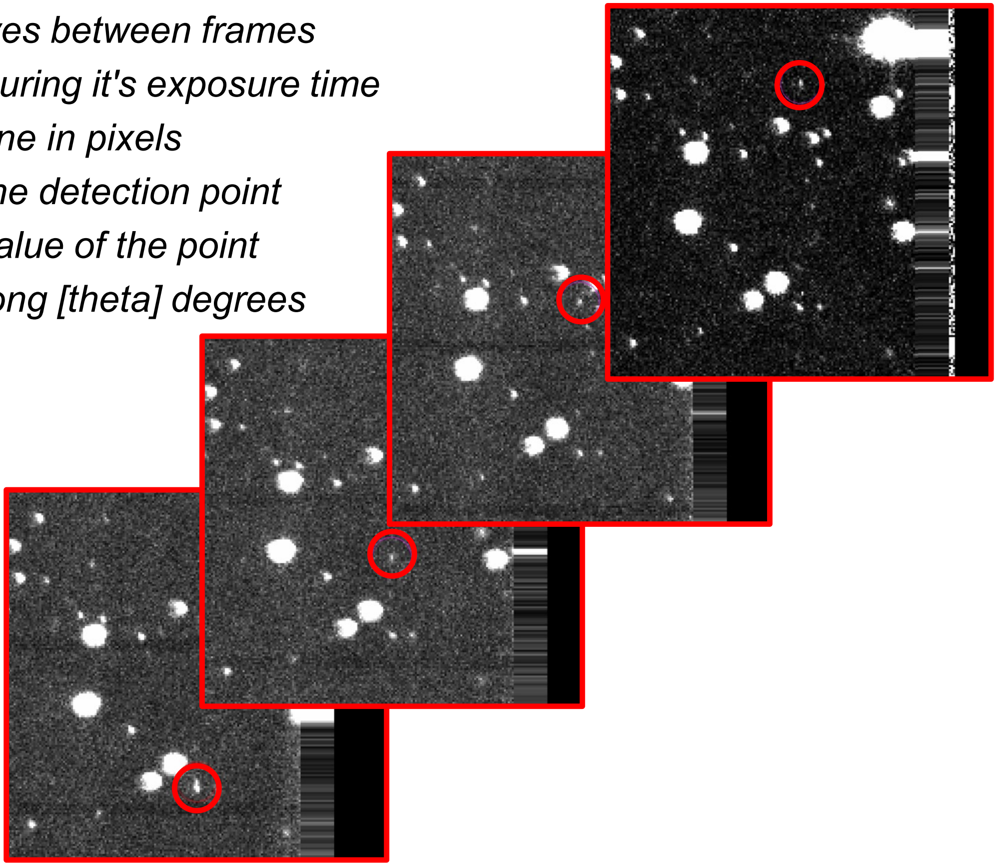




CSS has been successful with limited resources. Can AI improve performance?

Data Types

- Image data
  - *Each frame covers 5 square degrees*
  - *An observation consists of four 30 second exposures separated by 10 minutes*
  - *A smaller section of frame is presented to observers with candidate NEO circled in red*
- Metadata
  - *Angle of direction in degrees 0=North, 90=East, 180=South, 270=West*
  - *Average number of pixels that the object moves between frames*
  - *Average number of pixels the object moves during it's exposure time*
  - *Root mean square deviation from a straight line in pixels*
  - *Number of above threshold pixels that form the detection point*
  - *[FWHM] Measured full width half maximum value of the point*
  - *Measured elongation (pixels) of the object along [theta] degrees*
  - *[theta] The angle (degrees) of elongation*
  - *Measured magnitude of the object*
  - *SNR of object to background*
  - *Right Ascension of detection point*
  - *Declination of detection point*
  - *[x] Pixel location*
  - *[y] Pixel location*
  - *Object velocity*



What can we learn by combining both data types?

Problem Definition

- Given
  - *Three classes of objects (simplified)*
    - 0 = real NEO
    - 1 = real non-NEO (usually a main belt asteroid; sometimes a satellite)
    - 2 = reject (noise, background stars)
  - *Highly skewed data*
  - *NEOs and Rejects are not easily separable*
  - *Combination of images and metadata*
  - *Image sequence is important, but not really time series*
  - *Almost all of the image is background stars and contains no information*
  - *Lack of pretrained models*
  - *~800,000 labeled objects from one telescope (G96)*
  - *2 work months' of funding*

Label	% Candidate Objects
NEO	0.2%
Real non-NEO	68.7%
Reject	31.1%

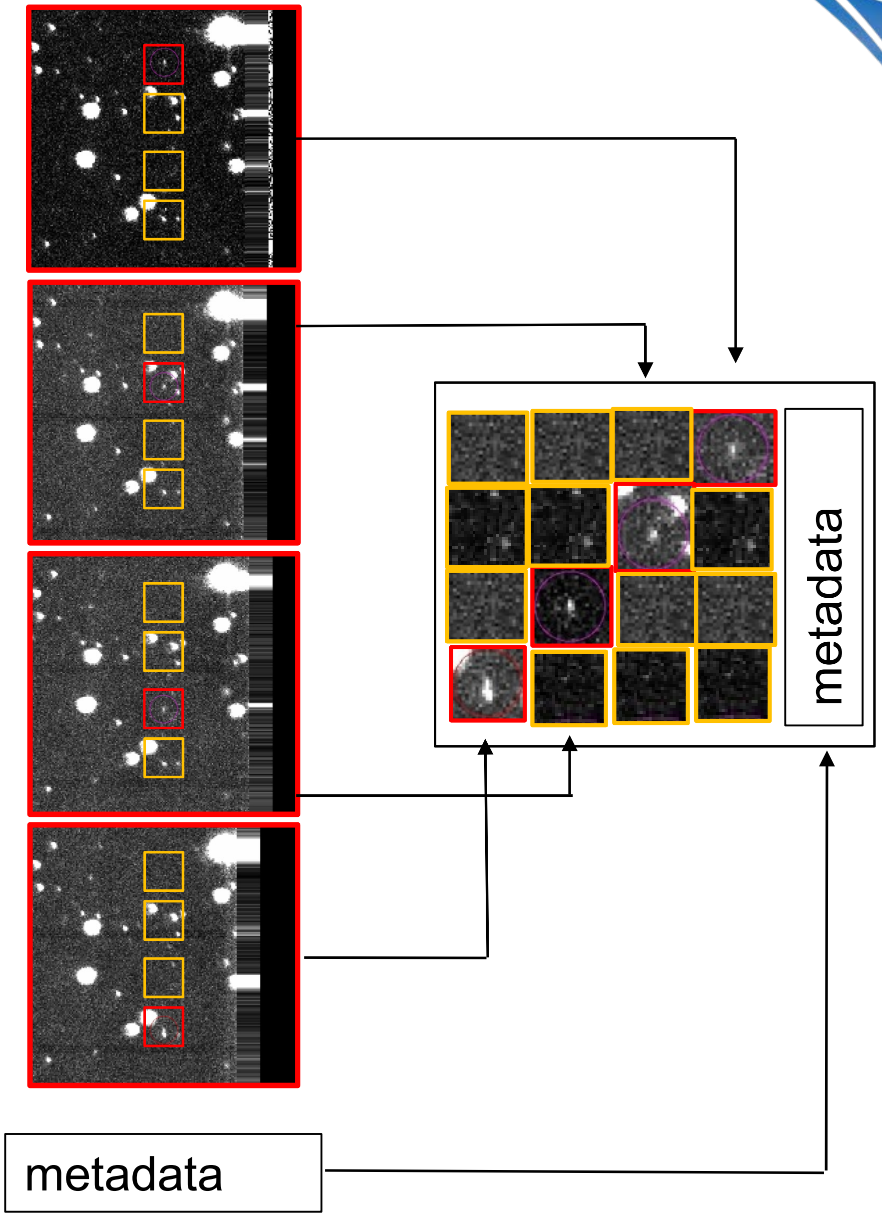
- Train a model to reorder candidate list such that objects likely to be classified as NEOs by a human observer are ranked near the top
  - *Reduce number of Rejects (false positives) screened by observers*
  - *Increase number of NEOs detected*

Goal is to augment, not replace, human observer

Data Pre-processing

Prepare to feed into neural network

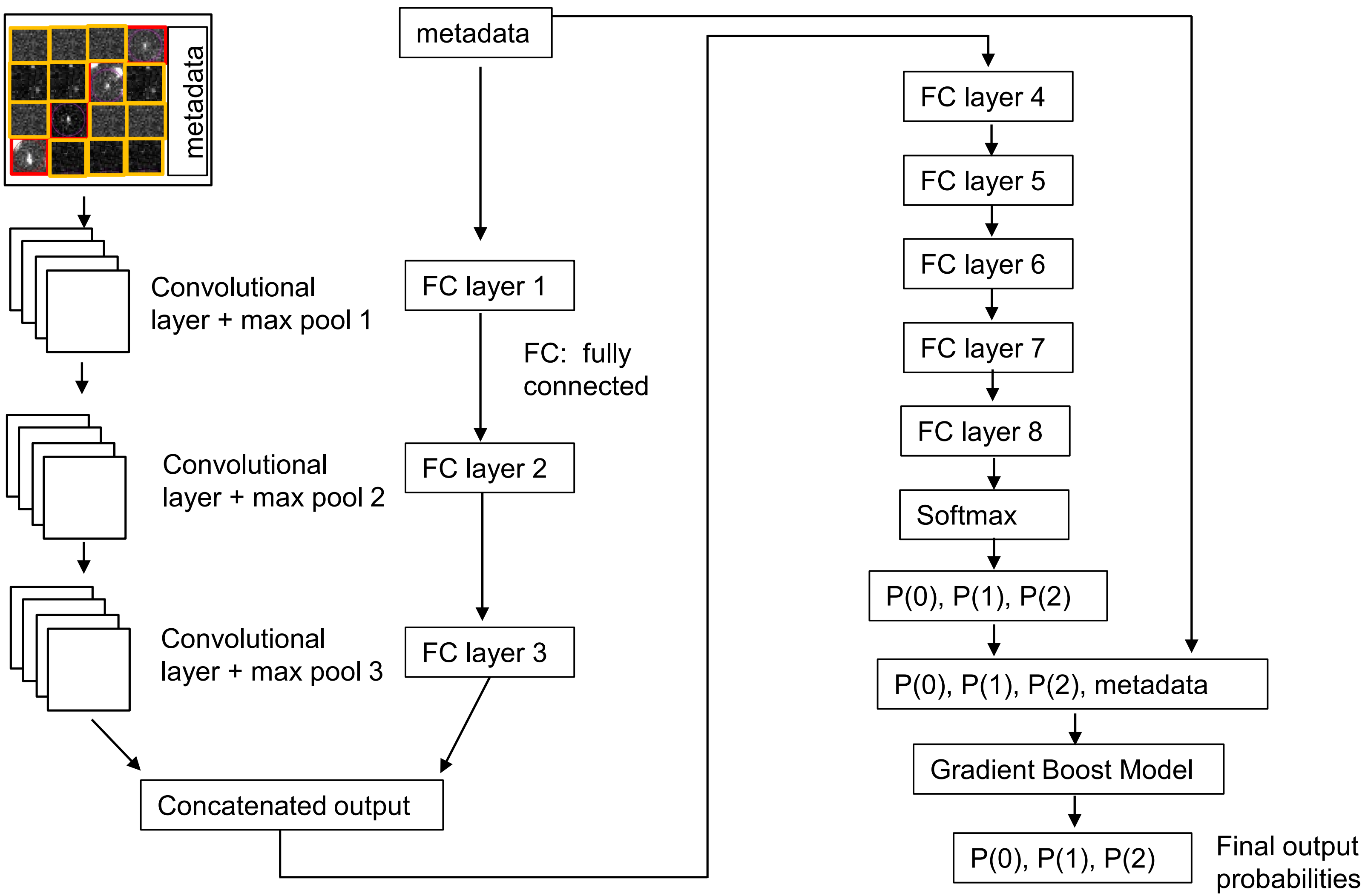
- Create 4x4 mosaic containing 60x60 pixel tiles showing time sequence from 4 frames
  - *Preserve order*
  - *Remove extraneous information to avoid confusing neural network*
  - *Learn to reject sequences of fixed stars and noise*
- Normalize pixel values from (0,255) to (-1, 1)
- Append metadata



Preprocessing is important for network performance

Model

Multimodal Neural Network (MNN) and Gradient Boost Model

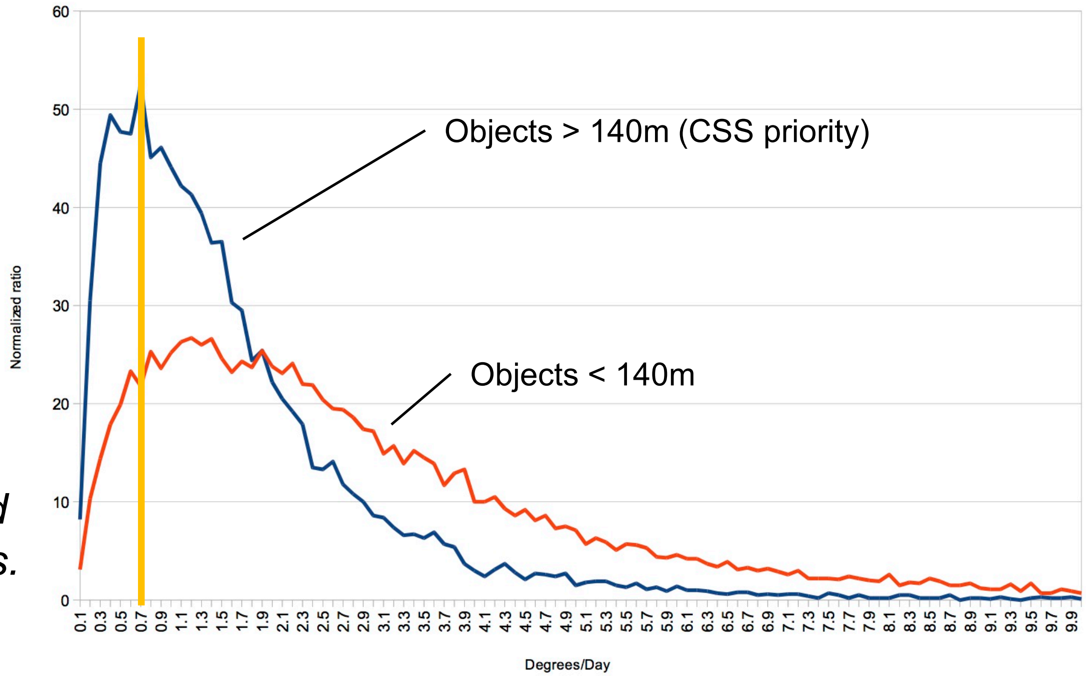


Hybrid model developed using Tensorflow and XGBoost Python libraries

Training and Results

- Hardware and software stack
  - *Hardware: NVIDIA Tesla P100, 56 cores, 1024 GB RAM, centOS 7.6.*
  - *Software: Python, Tensorflow, Anaconda, XGBoost*

- Training
  - *MNN trained on 537k objects, tested on 106k*
  - *GBM trained on 725k, tested on 86k*
- Reorder list
  - *AeroScore = 100*P(0) + P(1)*
- Results
  - *New algorithm detections biased towards slower main belt objects.*
  - *After modifications to correct for bias towards slow movers, CSS analysis showed the Aerospace algorithm providing a 10.7% increase in identified NEOs.*



Plot of simulated NEO population showing normalized brightness vs. velocity in degrees/day. Peak occurs at about 0.8 degrees per day with most NEOs moving faster. New algorithm was biased towards slower objects, which would miss most NEOs. After adjusting for this bias, more NEOs can be detected with new algorithm.

AI shows potential 10.7% increase in NEOs detected. (Still needs to be validated.)

Lessons Learned and Future Work

- Data preprocessing before training neural network is essential
  - *Initial results without preprocessing were not encouraging*
  - *Background detection could improve performance*
- Need to investigate means of training on highly skewed data
  - *Data augmentation*
  - *Synthetic data*
- Network architecture is important
  - *Networks designed specifically for change detection between images*
- Deployment to operations needs more work
  - *Tensorflow is a tricky package with many dependencies on other software libraries*
  - *Porting model from centOS 7.6 to CSS servers running centOS 6.5 did not work*
  - *Containerization using Docker and Singularity did not work due to difficulty of accessing GPU on target server*
  - *Model can be run without GPU; validation on target server pending*

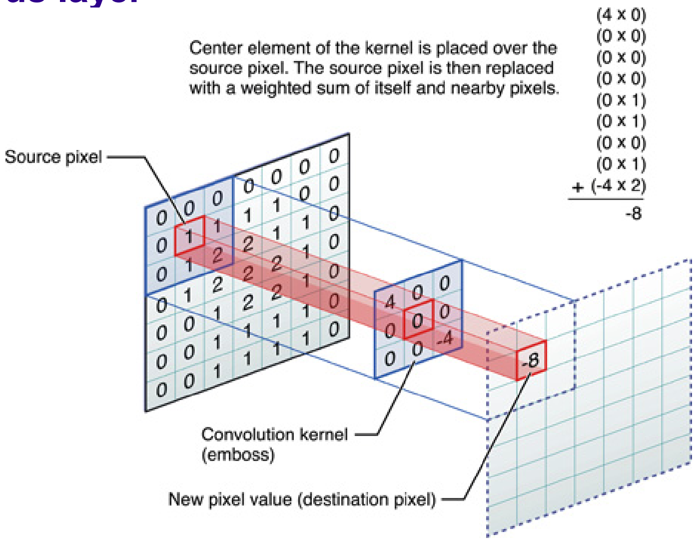
Gains in NEO detection using more advanced techniques could be substantial.

Backup

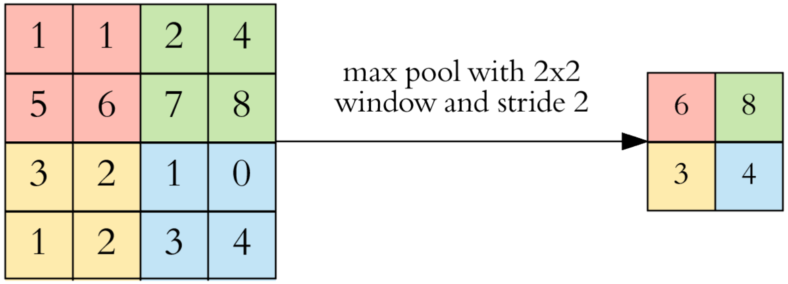
Convolutional neural networks (Yann LeCun 1990)

"...much easier to train and generalize much better..." – LeCun, Hinton

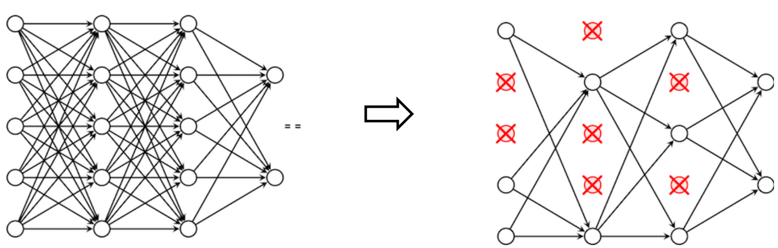
Convolutional layers detect local features from previous layer



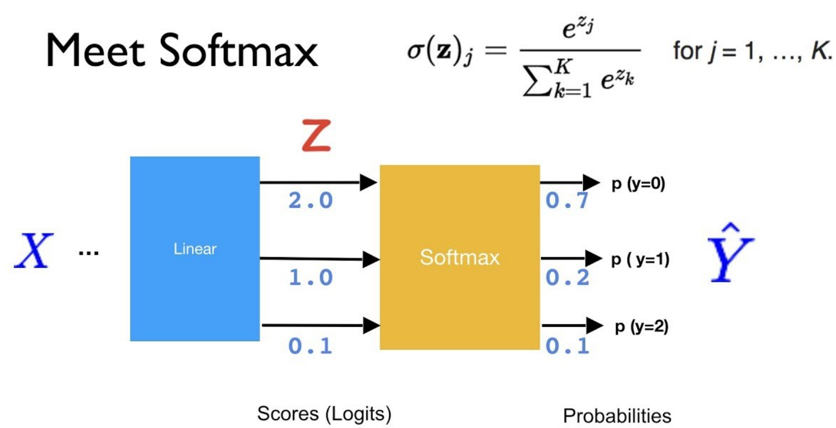
Max pool layers merge semantically similar features into one



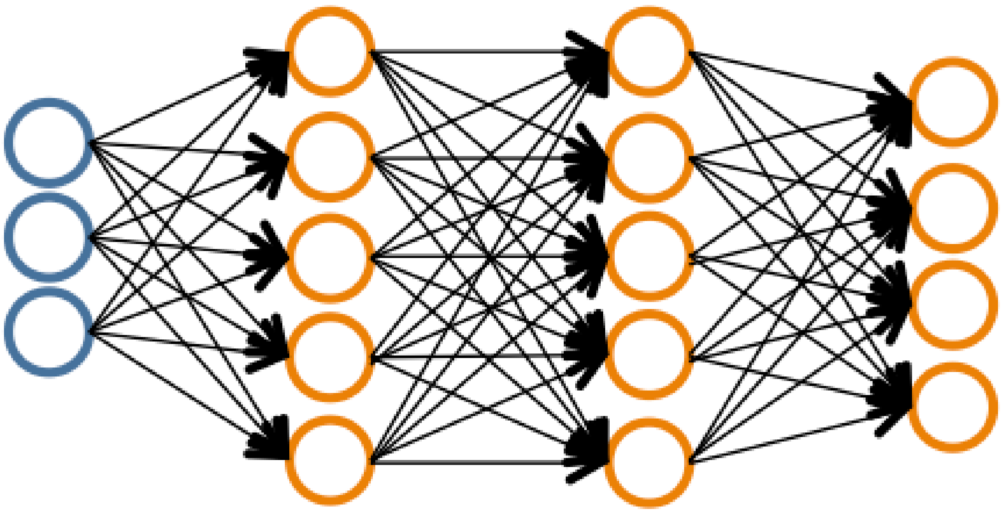
Dropouts prevent overfitting



Softmax for output (appropriate for classification)

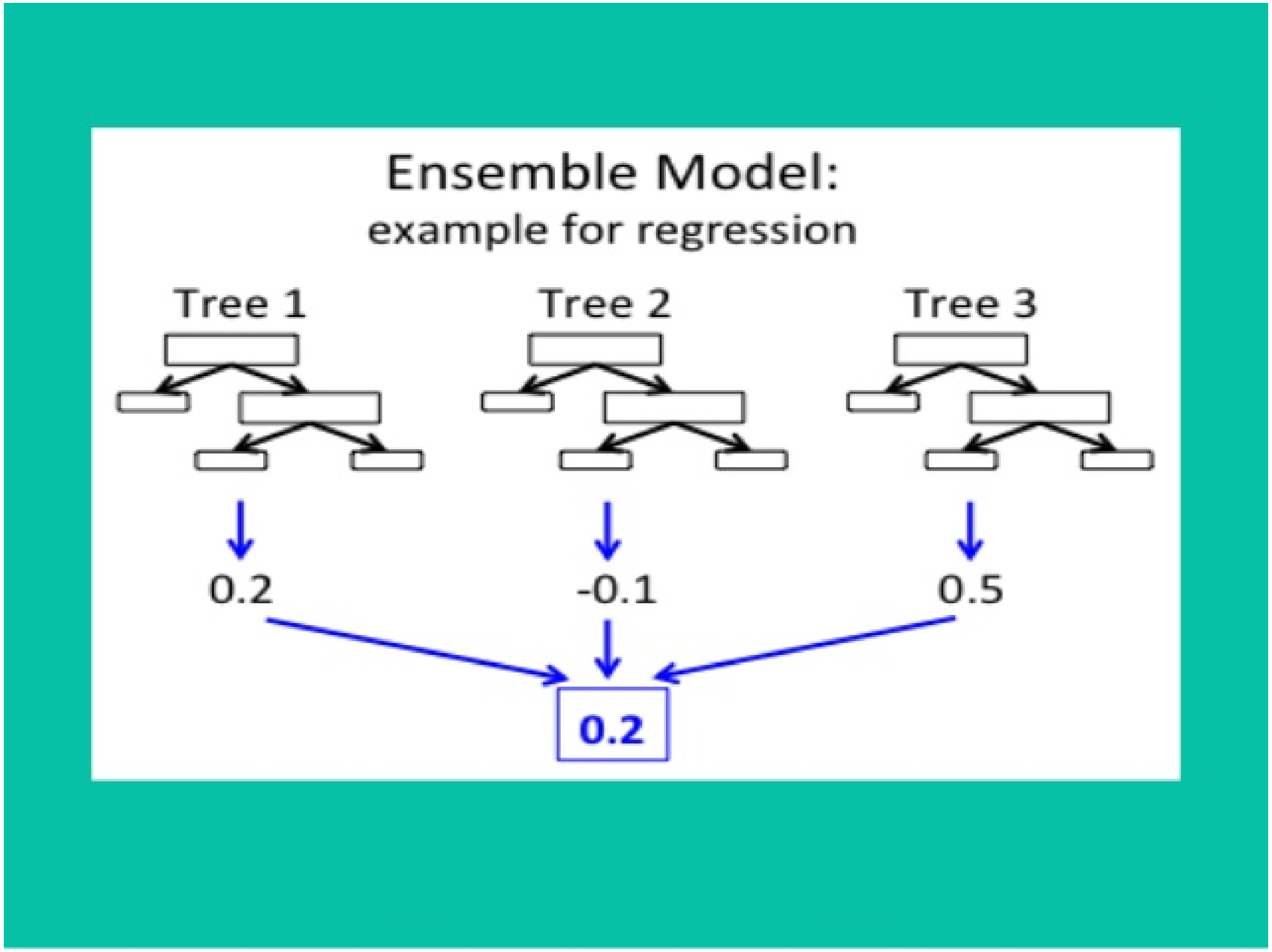


Fully Connected Layers



Gradient Boost Model

A type of ensemble tree method



Fit a bunch of decision trees using subsets of data. Each decision tree is a weak predictor but they can be combined to create a strong predictor.