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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

• 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.

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**

Center element of the kernel is placed over the source pixel. The source pixel is then replaced with a weighted sum of itself and nearby pixels.

**Max pool layers merge semantically similar features into one**

Max pool with 2x2 window and stride 2

**Dropouts prevent overfitting**

**Softmax for output (appropriate for classification)**

\[
\sigma(z)_j = \frac{e^{z_j}}{\sum_{k=1}^{K} e^{z_k}} \quad \text{for } j = 1, \ldots, K.
\]

**Meet Softmax**

Scores (Logits)  |  Probabilities
---|---
2.0  |  0.7  |  p (y=0)
1.0  |  0.2  |  p (y=1)
0.1  |  0.1  |  p (y=2)
Fully Connected Layers
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.