Machine Learning for Space Situational Awareness

AMOS 2018 – Short Course

Code Examples

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Outline

- **Tooling (< 5m): Software and libraries for ML/DL**
- **Dimensionality Reduction (10m): PCA, TSNE, UMAP**
- **Supervised Learning (60m):**
  - Tabular Data: TLE example with fully-connected network (MLP)
  - Time-Series Data: Asteroid light curve example with 1D-CNN
- **Break (10m)**
- **Unsupervised Techniques (40m)**
  - Transfer Learning
  - Self-Supervision: Auto-Encoders and Auto-Encoder Style Algorithms
  - Domain Adaptation on Synthetic Data

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Disclaimer

- **The following examples illustrate some common machine learning workflows. They aren't intended as optimal solutions to real problems.**
- **Despite the slide footer, nothing presented here is actually "CACI Proprietary Information"**
- **You can access the code here:**
  - https://github.com/PJ7668/ml-for-ssa
  - The examples should all be runnable once you have:
    - Installed Anaconda (popular python distribution for data science and machine learning)
    - Downloaded the data

Tooling for Machine/Deep Learning

- **Primary Deep Learning platforms:**
  - TensorFlow (Google)
  - PyTorch / Caffe2 (Facebook with support from Nvidia)
  - MXNet (apache project with Amazon support)
- **Best choice depends on your goal:**
  - Fundamental Research
  - Proof-of-concept
  - Operational Pipeline
  - Deployment to Embedded System
- **Use whatever environment you feel productive in:**
  - R (keras interface)
  - MATLAB (Neural Networking Toolkit)
  - Python (keras+tensorflow or pytorch)
- **Hardware:**
  - There may come a time you need a GPU, but you don't need it to get started.
  - When you do, you'll almost certainly be wanting Nvidia hardware running their CUDA libraries.

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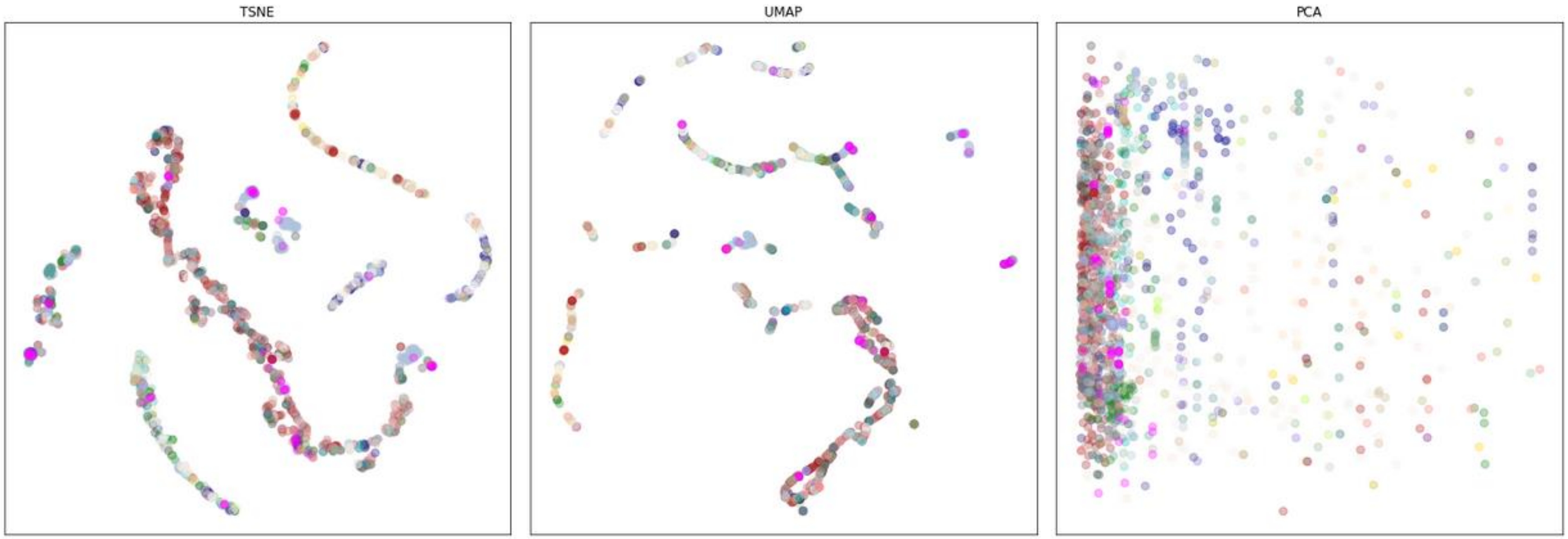
Dimensionality Reduction

- **ML tasks can have many possible input features.**
- **Deep Learning Rule of Thumb:**
  - Avoid hand-selecting or engineering features.
  - When practical, give neural network access to raw data to identify its own combinations of features.
- **However, using "all the features" is not always practical. Dimensionality reduction techniques can be useful for:**
  - Visualization
  - Reduce the feature space

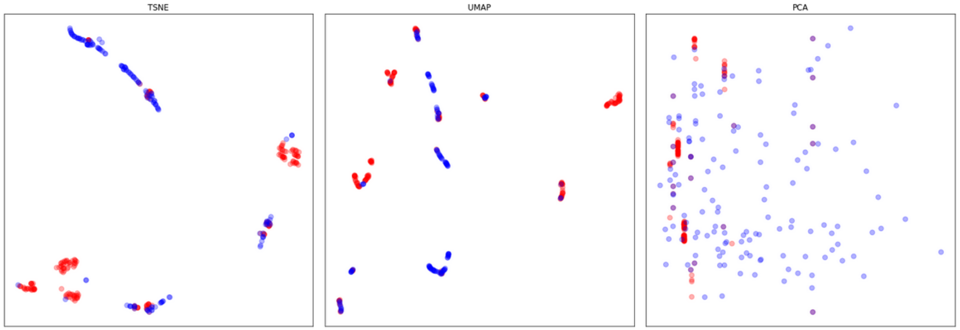
Dimensionality Reduction

	arg_perigee	bstar	excentricity	group	inclination	mean_anomaly	mean_motion	mean_motion_derivative	orbit	right_ascension
	344.9211	0.000000e+00	0.000220	ses	0.0117	192.3938	1.002720	-9.800000e-07	328	182.7004
	240.3986	0.000000e+00	0.692405	science	70.7112	0.3731	0.378005	6.190000e-06	659	281.4812
	47.2687	0.000000e+00	0.000032	intelsat	0.0269	160.3231	1.002700	3.900000e-07	5463	115.9600
	174.5702	0.000000e+00	0.000298	intelsat	0.0329	192.7488	1.002723	-1.250000e-06	4866	352.6984
	281.6462	0.000000e+00	0.000444	geo	0.0999	283.1222	1.002717	1.100000e-06	4522	275.0218
	269.9895	2.424900e-05	0.001328	argos	99.1391	89.9755	14.123839	-2.000000e-08	68470	282.6112
	307.8352	2.774000e-05	0.001298	education	97.5885	52.1692	14.908850	2.200000e-06	6182	144.7883
	238.0707	0.000000e+00	0.000171	geo	0.0623	265.3074	1.002718	7.000000e-07	4721	280.2496
	142.3965	3.386900e-05	0.001046	amateur	98.6875	217.7946	14.221306	3.100000e-07	78718	253.0090
	14.1533	-3.579400e-08	0.001436	resource	6.0029	345.9173	14.765825	6.400000e-06	15832	324.8697
	102.8129	4.843400e-05	0.000960	planet	97.4436	257.4181	15.246237	1.124000e-05	8380	309.6436
	57.8069	0.000000e+00	0.006835	sarsat	56.4768	302.9085	2.005516	-5.100000e-07	8640	326.5501
	83.0369	1.881400e-05	0.000260	iridium-NEXT	86.3968	277.1123	14.342186	7.200000e-07	2241	39.1703
	129.1498	2.141600e-05	0.000184	planet	97.4114	230.9901	15.212770	4.100000e-06	4644	358.5258
	63.5433	1.587800e-04	0.000271	cubesat	51.6345	296.5842	15.711176	1.988000e-04	6587	330.6930
	209.0278	0.000000e+00	0.001739	glo-ops	64.1831	216.3147	2.130987	3.000000e-07	2923	289.8220
	67.7021	0.000000e+00	0.000038	sarsat	3.0717	53.9275	1.002744	9.000000e-08	4655	71.6448
	9.0699	2.485900e-05	0.001057	noaa	98.7677	351.0670	14.258733	1.400000e-07	5604	262.0679
	307.4328	2.095800e-05	0.001307	engineering	97.5881	52.5701	14.908546	1.530000e-06	6181	144.6987
	84.8071	4.285600e-05	0.000222	iridium	86.4018	275.3378	14.342184	1.400000e-06	7515	165.6108

- **Sample TLE data.**
- **9 real valued fields**
- **1 categorical field (group)**
- **"group" comes from the way CelesTrak categorized the given TLE.**



- **2D embeddings of the 9D feature vectors**
- **Group field mapped to color**
- **(right) Just "planet" and "resource" groups**



- **The visualizations suggest we should be able to make some better-than-random guesses about the group field based just on the numeric fields.**

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Classification

Goal: Predict group field based on 9 TLE derived, numeric fields.

Machine Learning Work Flow

1. **Split data into train, test, and validation sets**
2. **Choose a metric (preferably a single, real-valued number)**
3. **Choose a model**
    1. Train model on train set
    2. Compute metric on test set
    3. Adjust model and repeat
4. **Evaluate model on validation set**

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Switch to TLE Notebook

Summary of TLE Example

- **Train/Test/Validation Sets:**
  - Train: Data used to update model parameters.
  - Test: Data used to update model hyper-parmeters.
  - Validation: Data used to measure performance of selected model.
- **Training Vocabulary:**
  - Epoch – one full pass through test train set
  - Batch Size – how many examples to evaluate at once. Typically, a gradiant is computed on this data.
  - Loss – *differentiable* function comparing predictions and targets: model(x) vs y.
  - Stochastic Gradient Descent (SGD) – the algorithm for efficiently updating model parameters by computing partial derivatives of loss(model(x), y) over a batch of samples.

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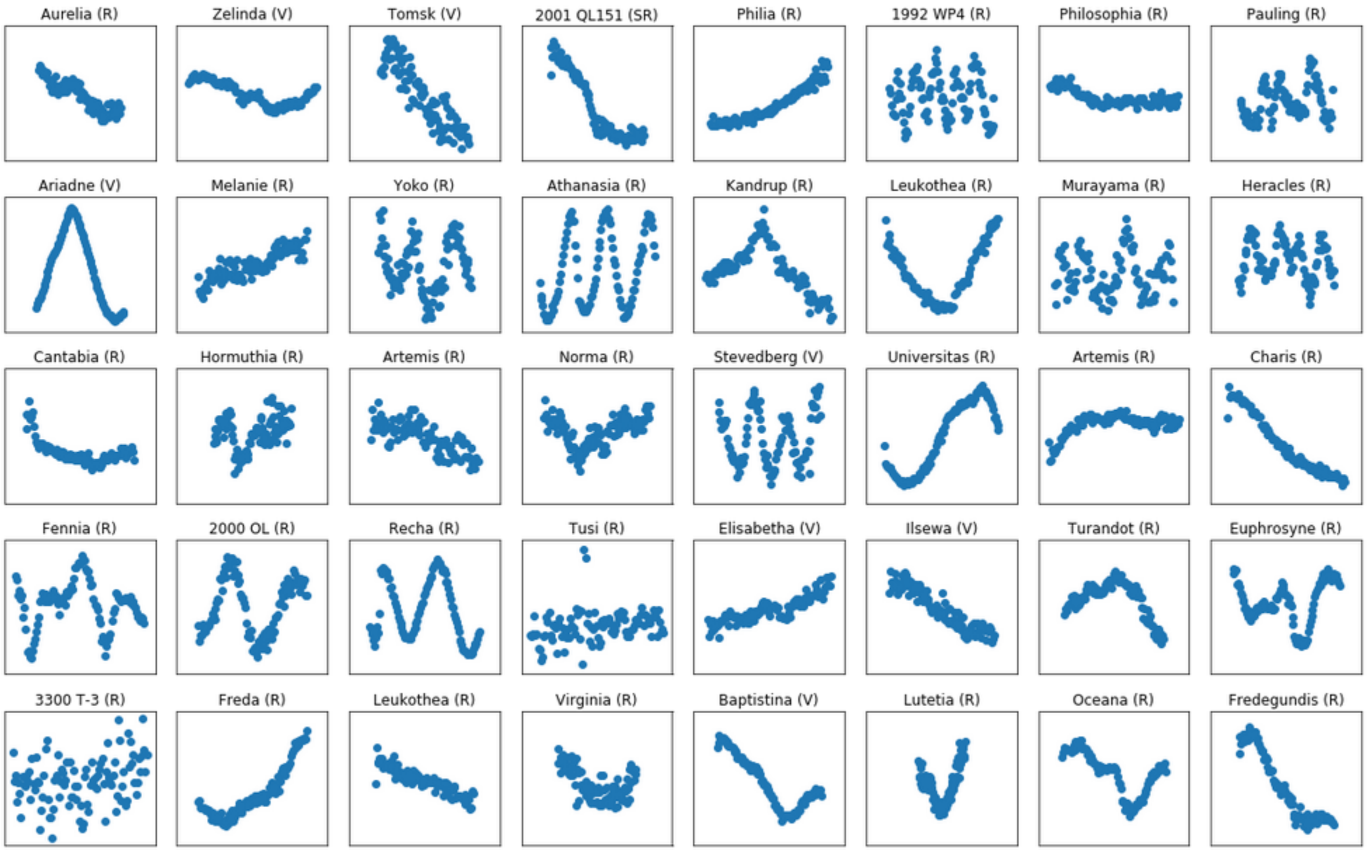
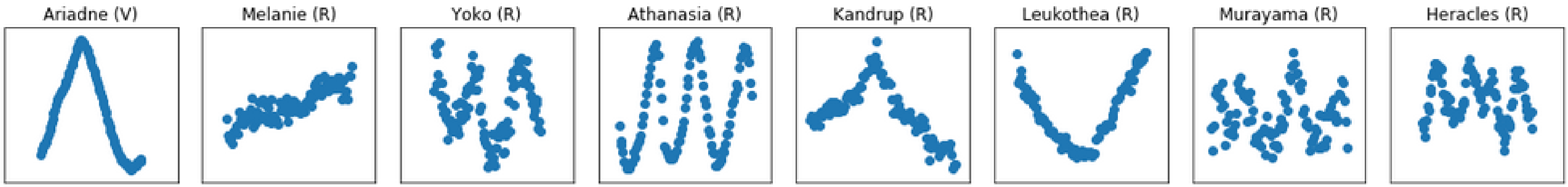
Summary of TLE Example

- **Avoid hand-selected/engineered features (at least initially)**
- **Split train/test data based on some deterministic criteria**
  - For example, test samples are precisely those for which SAT_ID % 5 == 0. This helps to avoid accidently letting the same or equivalent examples fall into your train and test sets.
- **Be very careful with metrics and class imbalance.**
  - For example, if 95% of your data belongs to the same class, reporting a 96% accuracy needs some qualifications.
- **Identify a single-number metric to help simplify model comparisons.**
- **Normalize your feature data.**
- **Focus on the simplest version of a problem first and avoid extensive hyperparameter optimization until you can demonstrate that the most basic thing is working.**
- **Make sure the model is learning the training data before even worrying about the test data. If your model can't even memorize the training data well, either your problem is going to work or something else is broken.**
- **Even if you're monitoring accuracy, looking at a confusion matrix is almost always helpful to understand how your model is performing.**

Convolutional Neural Networks



- **Example light curves from alcdef.org: Asteroid Lightcurve Photometry Datab**



- **Goal: Recognize asteroids based just on their light curves.**
- **Our features are translationally invariant in the sense that:**
  - If we happened to start collecting the light curve a few seconds earlier or later, then we would still be looking at the same object.
  - Likewise, if there was some property near the beginning of the light curve that was important for asteroid recognition, the same property located in the middle or near the end, should be just as important.
- **This is the motivation behind convolutional neural networks.**

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Convolutional Neural Networks

- **Discuss CNN Diagram**
- **Switch to Asteroid Light Curve Notebook – Part 1**

Summary of Asteroid Example

- **Outside knowledge about the structure of your data can greatly improve model performance and/or training speed.**
- **Helpful to have a baseline model for comparison. This could be:**
  - A "classical" ML algorithm like logistic regression or SVM.
  - A non-ML algorithm already being used to solve the problem.
  - How well a human can solve the problem (objective or subjective).
  - How well a human says an algorithm would need to perform for them to find it useful.
- **Remember there exists a Bayes Rate (performance of the "Bayes Model" that knows the "true" generation scheme)**
- **Helpful to understand how a random model or a model that has only learned the background distribution will perform.**
- **Neural networks can be adaptable to multi-modal input.**
  - Combining different types of data into an analytic model can quickly become intractable, but it is fairly straightforward for a neural network.
  - Consider adding auxiliary tasks, i.e. predict additional outputs that you might not care about but could provide additional relevant "training signal" to improve performance on the primary task. For example, in our light curve example, we might predict the Filter value or the sampling rate as an auxiliary task.
- **RNNs can be a natural fit for time-series data**
  - They are SOTA in some cases (e.g. natural language processing)
  - In practice, they tend to be much more finicky than CNNs.
  - There is some evidence that CNNs with attention mechanisms are generally a better choice.

Hard Lessons about Data and ML

- **You'll spend 90% of your time tending to your data.**
  - ML techniques are cheap and disposable.
  - Data pipelines are far more important.
- **Be suspicious of your data.**
- **Be suspicious of people who give you data.**
  - It's easy to overlook biases in your data that were never a problem when humans or non-adaptive algorithms were the primary consumers of it.
  - People will greatly overestimate their ability to perform the task they want you to automate.
- **Be suspicious of yourself. When a model is working well, assume you've messed something up:**
  - Misunderstood your class imbalance (e.g. Case 1 is 95% of your data)
  - Contaminated your test data with training data
  - Included some "feature" that amounts to cheating (e.g. one of the features is basically the target value)

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Unsupervised Learning

Unsupervised Learning

- **Supervised learning uses known target values and a differentiable loss function to drive learning.**
- **However, we often have:**
  - Few or no target values because they are difficult/expensive to collect.
    - Related to zero-shot or low-sample learning.
  - No target values because we don't really know what we're looking for.
    - We may suspect that there are some latent factors that explain observations but we haven't gotten far enough to express what those factors are, much less actually measure them.
- **Very active area of ML research but remains a hard problem.**

Unsupervised Learning Techniques

- **Transfer Learning**
  - Parameter initialization schemes have been greatly improved NN training.
  - You can often do even better by training a set of weights (parameters) on another data set and using these trained weights as the parameter initialization for your problem.
  - Very effective technique in computer vision.
  - Simple NN + transfer learning is considered the benchmark approach for many problems.
- **Domain Adaptation on Synthetic or Out-of-Domain Data**
  - NNs tend to be sensitive to low-level features that a human would know are irrelevant to the problem (e.g. differences in quantization or compression artifacts)
  - Domain adaptation can refer to
    - Transforming data from one domain to another (e.g. from sensor A to sensor B)
    - Modifying a training process in such a way that performance generalizes well to a domain for which you have no labeled data (e.g. train on data from sensor A but model still performs well on sensor B).
- **Self-Supervision: Auto-Encoder Style Algorithms**

Unsupervised Learning: Self-Supervision

- **Turn unsupervised problem into a supervised problem by inventing a surrogate target value. This usually amounts to solving a problem you don't actually care about but hoping a network will learn something useful in the process.**
- **Example 1: Auto-Encoder**
  - Target values are the input features themselves
  - Introduces a low-dimensional "pinch point" in the network
  - A network able to recreate its input with high fidelity must have learned a low-dimensional representation of the data.
- **Example 2: Unsupervised Feature Learning**
  - https://arxiv.org/abs/1805.01978
    Unsupervised Feature Learning via Non-Parametric Instance-level Discrimination
  - Treats unsupervised learning as a classification problem where every example is the sole representative of its own class. This can lead to many 1000s of classes.
  - Like an auto-encoder, pinch point forces network to learn low-dimensional representation of the data.

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