Advanced Machine Learning in SPL with the Machine Learning Toolkit

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Software Engineer, Splunk

.conf2016

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Who am I?

- Splunker for 2 years, based in San Francisco
- Engineering lead for...
 - ML Toolkit and Showcase App
 - ITSI Anomaly Detection and Adaptive Thresholding features
 - Splunk custom search command interface
- Initial author of fit/apply commands in ML Toolkit
- Die-hard Longhorns fan





Agenda

- Machine Learning + Splunk
- ML-SPL: Machine Learning in SPL
 - What it is
 - How it works
- Overview of Algorithms and Analytics available in ML-SPL
- Tips for Feature Engineering in SPL
- Wrap up



Machine Learning + Splunk

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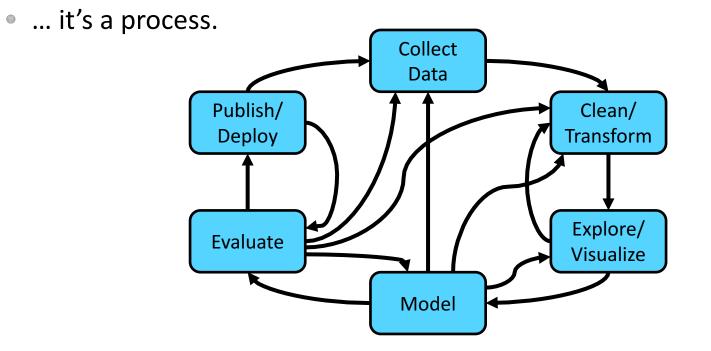
Machine Learning is Not Magic

• ... it's a process.

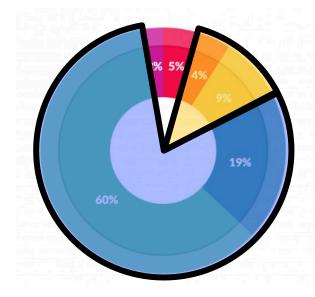
- The process starts with a question:
 - How many requests do I expect in the next hour?
 - How likely is this hard drive to fail in the near future?
 - Am I being hacked?
 - Is it unexpected for Joe to login to the bastion host at 2am?



Machine Learning is Not Magic







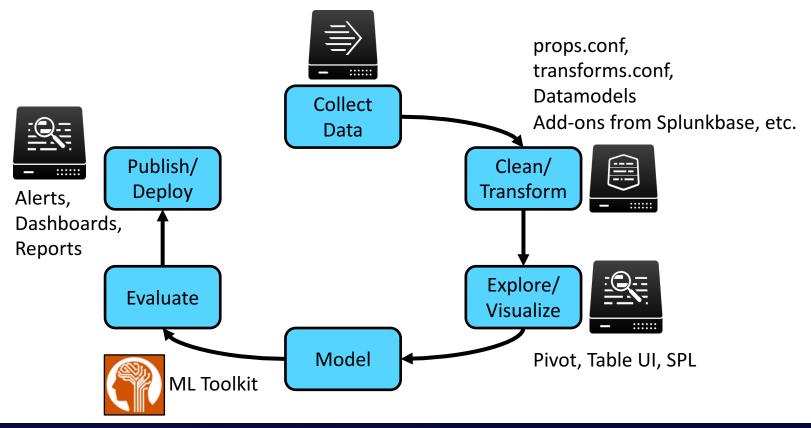
Data preparation accounts for about 80% of the work of data scientists

What data scientists spend the most time doing

- Building training sets: 3%
- Cleaning and organizing data: 60%
- Collecting data sets; 19%
- Mining data for patterns: 9%
- Refining algorithms: 4%
- Other: 5%



Splunk for Data Preparation





ML-SPL: Machine Learning in SPL

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ML-SPL: What is it?

- A suite of SPL search commands specifically for Machine Learning:
 - fit
 - apply
 - summary
 - listmodels
 - deletemodel
 - sample
- Implemented using modules from the Python for Scientific Computing add-on for Splunk:
 - scikit-learn, numpy, pandas, statsmodels, scipy

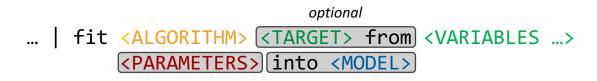


ML-SPL Commands: A "grammar" for ML

- Fit (i.e. train) a model from search results
- Apply a model to obtain predictions from (new) search results
 ... | apply <MODEL>
- Inspect the model built by <ALGORITHM> (e.g. display coefficients)
 | summary <MODEL>



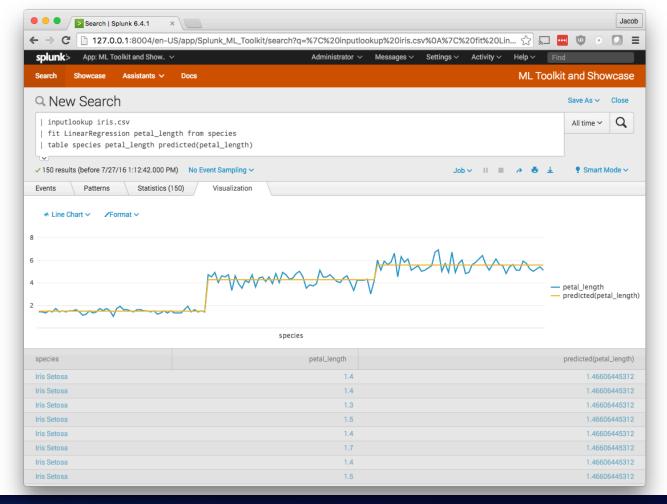
ML-SPL Commands: fit



Examples:

- ... | fit LinearRegression
 system_temp from cpu_load fan_rpm
 into temp_model
- ... | fit KMeans k=10
 - downloads purchases posts days_active visits_per_day
 into user_behavior_clusters





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- 1. Discard fields that are null for all search results.
- 2. Discard non-numeric fields with >100 distinct values.
- 3. Discard search results with any null fields.
- Convert non-numeric fields to binary indicator variables (i.e. "dummy coding").
- 5. Convert to a numeric matrix and hand over to <ALGORITHM>.
- 6. Compute predictions for all search results.
- 7. Save the learned model.

... | fit LogisticRegression field_A from field_*

1. Discard fields that are null for all search results.

| field_A | field_B | field_C | field_D | field_E |
|---------|---------|---------|---------|-------------|
| ok | 41 | | red | 172.24.16.5 |
| ok | 32 | | green | 192.168.0.2 |
| FRAUD | 1 | | blue | 10.6.6.6 |
| ok | 43 | | | 171.64.72.1 |
| | 2 | | blue | 192.168.0.2 |

Target Explanatory Variables...



... | fit LogisticRegression field_A from field_*

2. Discard non-numeric fields with >100 distinct values.

| field_A | field_B | field_D | field_E |
|---------|---------|---------|-------------|
| ok | 41 | red | 172.24.16.5 |
| ok | 32 | green | 192.168.0.2 |
| FRAUD | 1 | blue | 10.6.6.6 |
| ok | 43 | | 171.64.72.1 |
| | 2 | blue | 192.168.0.2 |

Target Explanatory Variables...



... | fit LogisticRegression field_A from field_*

3. Discard search results with any null fields.

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|---------|---------|---------|--|
| field_A | field_B | field_D | |
| ok | 41 | red | |
| ok | 32 | green | |
| FRAUD | 1 | blue | |
| ok | 43 | | |
| | 2 | blue | |

| Target | Explanatory Variables |
|--------|-----------------------|
|--------|-----------------------|



... | fit LogisticRegression field_A from field_*

4. Convert non-numeric fields to binary indicator variables.

| 0 | | | | | | |
|---------|---------|-------------|--------|-------|--|--|
| field_A | field_B | field_D=red | =green | =blue | | |
| ok | 41 | 1 | 0 | 0 | | |
| ok | 32 | 0 | 1 | 0 | | |
| FRAUD | 1 | 0 | 0 | 1 | | |

Target Explanatory Variables...



... | fit LogisticRegression field_A from field_*

5. Convert to a numeric matrix and hand over to <ALGORITHM>.

$$y = [1, 1, 0] \qquad X = [[41, 1, 0, 0], \\ [32, 0, 1, 0], \\ [1, 0, 0, 1]]$$

e.g. for Logistic Regression:

$$\hat{y} = \frac{1}{1 + e^{-(\theta^T x)}}$$
 Find θ using maximum likelihood estimation.

Model inference generally delegated to scikit-learn and statsmodels. (e.g. sklearn.linear_model.LogisticRegression)

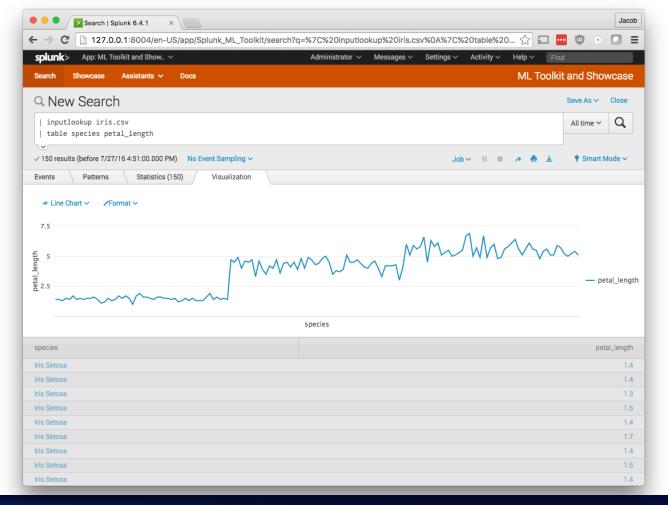


... | fit LogisticRegression field_A from field_*

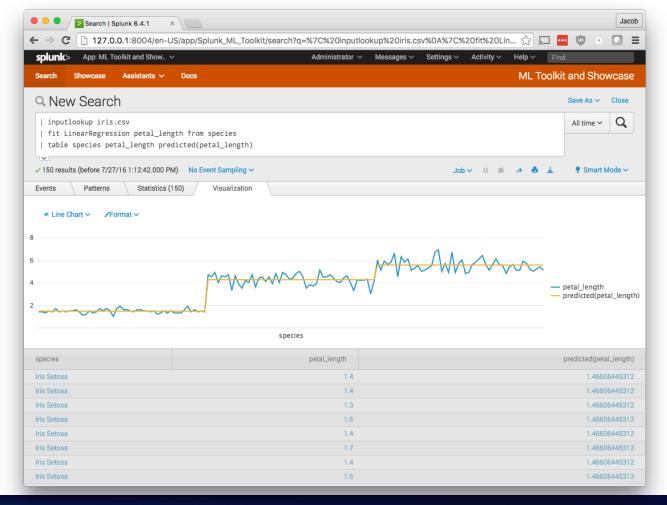
6. Compute predictions for all search results.

Prediction Target Explanatory Variables... predicted(field_A) field_A field_B field_C field_D field_E ok 41 red 172.24.16.5 ok ok 192.168.0.2 32 ok green FRAUD 1 blue 10.6.6.6 FRAUD ok 171.64.72.1 43 ok blue 2 192.168.0.2 FRAUD











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- ... | fit LogisticRegression field_A from field_* into logreg_model
- 7. Save the learned model.

Serialize model settings, coefficients, etc. into a Splunk lookup table.

- Replicated amongst members of Search Head Cluster.
- Automatically distributed to Indexers with search bundle.



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fit: Properties

• Each event is an "example" for the learning algorithm.

• Resilient to missing values. *(but be careful!)*

• Automatically handles categorical (e.g. non-numeric) fields.

- SAVES ITS WORK:
 - Learned model can be applied to *new, unseen* data with the **apply** command.



fit: Scalability

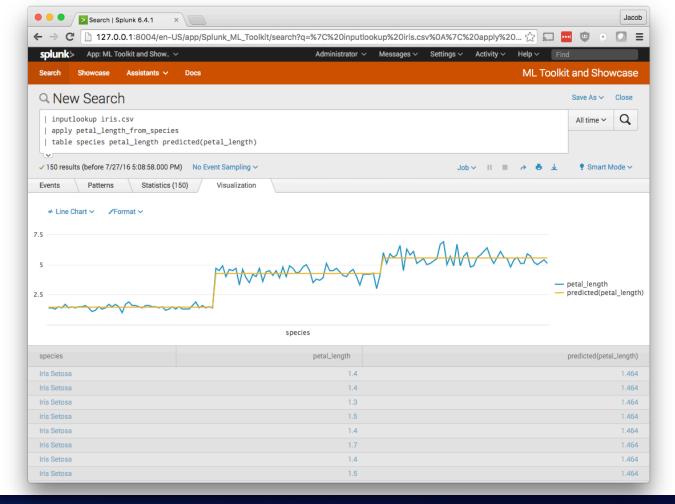
- Some algorithms are inherently *not scalable*.
 - e.g. Kernel-based Support Vector Machines is $O(N^3)$
- Input is sampled using *reservoir sampling*.
 - Per-algorithm sample reservoir size, typically 100,000 events
 - Configurable in **mlspl.conf**.
- Some algorithms support *incremental fitting*, e.g.: SGDRegressor, SGDClassifier, NaiveBayes
 - Use "partial_fit=t" option with fit command.
 - No sampling, no event limit!
- For the most part, you don't need to care.

ML-SPL Commands: apply

... | apply <MODEL>

Examples:

- ... | apply temp_model
- ... | apply user_behavior_clusters
- ... | apply petal_length_from_species





- 1. Load the learned model.
- 2. Discard fields that are null for all search results.
- 3. Discard non-numeric fields with >100 distinct values.
- Convert non-numeric fields to binary indicator variables (i.e. "dummy coding").
- 5. Discard variables not in the learned model.
- 6. Fill missing fields with 0's.
- 7. Convert to a numeric matrix and hand over to <ALGORITHM>.
- 8. Compute predictions for all search results.

... | apply fraud_model

4. Convert non-numeric fields to binary indicator variables.

| field_A | field_B | field_D=red | =green | =blue | =yellow |
|---------|---------|-------------|--------|-------|---------|
| ok | 41 | 1 | 0 | 0 | 0 |
| ok | 32 | 0 | 1 | 0 | 0 |
| FRAUD | 1 | 0 | 0 | 1 | 0 |
| | 41 | 0 | 0 | 0 | 1 |

Target Explanatory Variables...



... | apply fraud_model

5. Discard variables not in the learned model.

| field_A | field_B | field_D=red | =green | =blue | =yellow |
|---------|---------|-------------|--------|-------|---------|
| ok | 41 | 1 | 0 | 0 | 0 |
| ok | 32 | 0 | 1 | 0 | 0 |
| FRAUD | 1 | 0 | 0 | 1 | 0 |
| | 41 | 0 | 0 | 0 | 1 |

Target Explanatory Variables...



... | apply fraud_model

5. Convert to a numeric matrix and hand over to <ALGORITHM>.

$$y = [1, 1, 0, 1, ?]$$

$$X = [[41, 1, 0, 0], [32, 0, 1, 0], [1, 0, 0, 1], [41, 0, 0, 0]]$$

e.g. for Logistic Regression:

$$\hat{y} = \frac{1}{1 + e^{-(\theta^T x)}}$$
 Compute \hat{y} using θ found by **fit** command.



... | apply fraud_model

7. Compute predictions for all search results.

Prediction Target Explanatory Variables... predicted(field_A) field_A field_B field_C field_D field_E ok 41 red 172.24.16.5 ok ok 32 192.168.0.2 ok green FRAUD 1 blue 10.6.6.6 FRAUD ok 171.64.72.1 43 ok 41 yellow 192.168.0.2 ok



apply: Properties

• Learned models can be applied to *new, unseen* data.

| fit is to | apply

as

| outputlookup is to | lookup

• Resilient to missing values. (but, again, be careful!)

• Automatically handles categorical (e.g. non-numeric) fields.

apply: Scalability

• No limits.

- When possible, executes at the Indexing tier.
 - Fully parallelized; harness the CPU power of your Indexing Cluster.
 - Must set "streaming_apply = true" in mlspl.conf.



ML-SPL Commands: summary

... | summary <MODEL>

Examples:

- ... | summary temp_model
- ... | summary user_behavior_clusters
- ... | summary petal_length_from_species

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Algorithms and Analytics in ML-SPL

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Regression Algorithms (e.g. predict numeric fields)

- LinearRegression
 - ... including Lasso, Ridge, ElasticNet
- KernelRidge
- DecisionTreeRegressor
- RandomForestRegressor
- SGDRegressor

• All implemented with sklearn models.



Classification Algorithms (e.g. predict categorical fields)

- LogisticRegression
- DecisionTreeClassifier
- RandomForestClassifier
- SGDClassifier
- SVM
- Naïve Bayes
 - Including BernoulliNB and GuassianNB



Clustering Algorithms (e.g. group like with like)

- KMeans
- DBSCAN
- Birch
- SpectralClustering



Feature Engineering Algorithms (e.g. data pre-processing)

- TFIDF (term-frequency x inverse document-frequency)
 - Transform free-form text into numeric fields
- StandardScaler (i.e. normalization)
- FieldSelector (i.e. choose K best features for regression/classification)
- PCA and KernelPCA



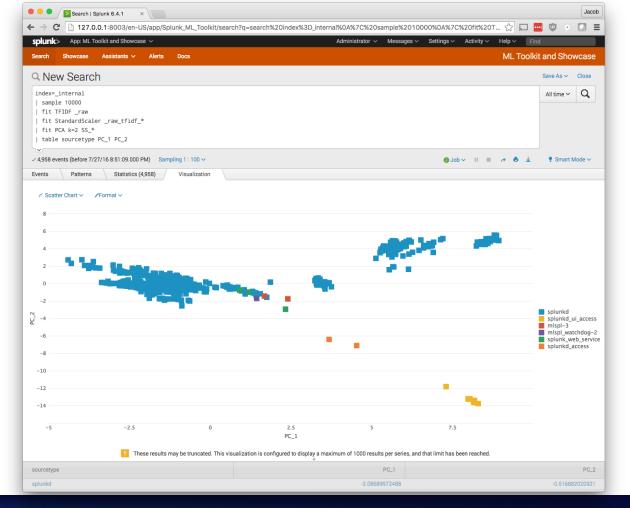
"Pipeline" Multiple Algorithms

- Example: Text Analytics
 - TFIDF to transform free-form messages into numeric fields, followed by...
 - KMeans to group similar messages
 - BernoulliNB to classify messages (e.g. according to sentiment)
 - PCA to visualize distribution of messages
 - ... | fit TFIDF message | fit Kmeans message_tfidf_* | ...
- Analogous to Pipeline concept from sklearn or Spark MLLib



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"Pipeline" Multiple Algorithms

• ML-SPL analytics are *stackable*.

• Very advanced ML use-cases are succinctly expressible.



Tips for Feature Engineering

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Tips for Feature Engineering

- Work on aggregates, not raw events.
 - DO NOT use fit on 1,000,000,000 events. DO use stats.
- Use eval to compute new features.

• Use streamstats to construct leading indicators.



Work on aggregates, not raw events

• Use **stats** and lookup tables to construct features:

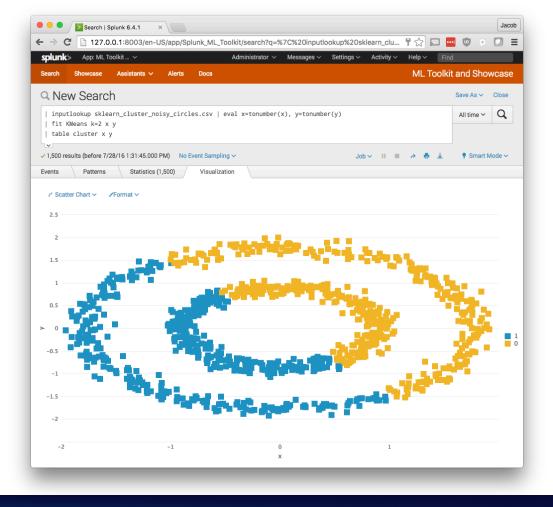


Use eval to compute new features

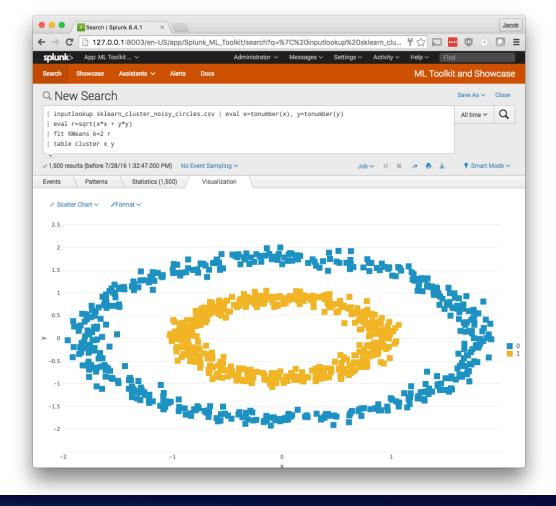
- Coerce numbers into categories by prepending a string:
 - ... | eval region_id = "Region " + region_id | ...

- Model interactions between features:
 - ... | eval X_factor = importance * urgency | ...
 - Use + for categorical fields, * for numeric

- Make non-linear features out of numeric values:
 - ... | eval temperature = pow(temperature,2) | ...
 - ... | eval latency = log(latency) | ...









Use **streamstats** for leading indicators





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What did we cover?

- Machine Learning + Splunk
- ML-SPL: Machine Learning in SPL
 - What it is
 - How it works
- Overview of Algorithms and Analytics available in ML-SPL
- Tips for Feature Engineering in SPL

What Now?

- Install the ML Toolkit from Splunkbase!
 - <u>http://tiny.cc/splunkmlapp</u>
- Don't miss Manish Sainani's or Adam Oliner's talks!

- Product Manager: Manish Sainani <msainani@splunk.com>
- Field Expert: Andrew Stein <astein@splunk.com>
- Me: Jacob Leverich <jleverich@splunk.com>

THANK YOU





fit: Misc. details

 Multi-class classification problems typically modeled as "one-vs-rest"

- Some algorithms do NOT support saved models, e.g.:
 - DBSCAN and SpectralClustering



ML-SPL Commands

- fit <ALGORITHM> <TARGET> from <VARIABLES ...> <PARAMETERS> into <MODEL>
 - Fit (i.e. train) a model from search results
- apply <MODEL>
 - Apply a model to obtain predictions from (new) search results
- summary <MODEL>
 - Inspect the model inferred by <ALGORITHM> (e.g., display coefficients)



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