

Announcing the Deep Learning Toolkit for Splunk with TensorFlow 2.0, PyTorch, NLP and Jupyter Lab Notebooks

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Agenda



About us

Intro to AI | ML | DL

MLTK Container

Use Cases

Wrap up



About Us

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Anthony Tellez | アンソニー テレズ

CISSP, CEH, CNDA, Sec+

- → | where _time@Splunk > 5y
- Previous:
 - U.S. Gov Contractor, Geospatial Analyst
 - Splunk Federal, PS Architect
- → Specializations
 - Cryptography
 - Information Security Red Team
 - Open Source Network Security: Suricata, Zeek
- → Field Data Scientist
 - Security & Fraud Analytics
 - Data Visualization & Statistics
- Responsible for the relationship between emerging technologies and global field organization: US, CAN, LATAM, APAC
- Al Evangelist for Splunk, presenting at various security & industry events
- https://github.com/anthonygtellez/
- → Fact: Spends 80% of the year on a plane traveling globally.





Philipp Drieger

- | where _time @Splunk > 4.5y
- Previous:
 - +15y in research, software development, visual arts
 - +3y SE across portfolio & domains in CEMEA & EE
- Specializations
 - Anomaly Detection, Data Mining, NLP, Advanced Analytics and Visualizations
 - Applied Data Science, Machine Learning, Graph Theory and Network Science
 - GPU Computing, Deep Learning
- Role @ Splunk
 - Staff Machine Learning Architect (Central EMEA)
 - Author of DGA App for Splunk
 - Author of <u>MLTK Container for Splunk</u>
 - Author of <u>Deep Learning Toolkit for Splunk</u>
 - Blog posts, conf talks, hackathons etc.
 - Ensure Customer Success with ML

Munich, Germany



Intro AI | ML | DL





"Humans are good at Learning... but we get lost in volume and detail."



Al v. Machine Learning

- "A Function that maps features to an output" = AI
- "A Function that learns patterns in your data without being explicitly programmed" = ML

Types of ML

Supervised Unsupervised Reinforcement





Field of Artificial Intelligence

Field of Machine Learning

Deep Learning





What ML & Al are not

Machine Learning is not Magic

Garbage Data = Useless Predictions

- Data Scientists spend <u>80% of their time</u> cleaning, munging and collecting data
- Throwing more data at an algorithm will not result in solving all of your SOC issues
- Machine Learning requires a solid understanding of statistics and the scientific method

ML & AI require you to <u>understand the</u> <u>fundamental business problem</u> you want to solve.





What ML & Al are not

Machine Learning is not Magic

ML is <u>not a replacement</u> for expert analysts, or engineers.

ML requires Subject Matter Experts to enhance security & IT operations.

Analysts are required to provide feedback to the models to adjust thresholding rules and <u>reduce</u> <u>false positives</u>.

If you need more examples check out some of the past conf talks:

- .conf18 Getting Your Data Ready for Machine Learning - Kristal Curtis
- .conf18 Using the Latest Features from the Splunk Machine Learning Toolkit to Create Your Own Custom Models – Harsh Keswani
- .conf18 Turning Security Use Cases into SPL – Marquis Montgomery





Machine Learning & Al

What does the scientific method look like in the IT & Security Space?

- Problem: DGA domains are computer generated pseudorandom character strings used by attackers, blacklisting an infinite number of domains is not feasible.
- Hypothesis: "Are there <u>patterns in</u> <u>domain generation algorithms</u> that can be exploited to identify newly generated domains as threats in real-time?"



Example Domains:

http://87hfdredwertyfdvvlkgdrsadm.net/af/GHFbfsalku65 http://87hfdredwertyfdvvlkgdrsadm.net/af/sdgLKJvgh http://wszystkodokuchni.pl/34f43



Machine Learning & Al

What does the Deep Learning Marketplace look like?

Not every problem can be solved with ML

- If you understand your underlying business problem and can clearly state your hypothesis... ML provides you a statistical framework for testing
- Deep Learning is designed to help customers leverage the power of more <u>advanced math &</u> <u>parallel processing</u> power.
- Deep Learning frameworks such as PyTorch, and Tensorflow can leverage both CPU & GPU resources to reduce training time.
- You still need to understand the problem you are solving to optimize the neural network's layers & hyperparameter tuning.



https://www.rtinsights.com/top-deep-learning-tools/



MLTK Container





Key Benefits of the MLTK Container



Seamlessly Integrate with Splunk Enterprise and Machine Learning Toolkit Workflows

Freedom of Code within Jupyter Lab Notebooks for Advanced Modelling with TensorFlow and PyTorch GPU accelerated Deep Learning for Compute Intensive Training Workloads



Integrated Architecture with Splunk's MLTK



GPU Accelerated Training of Deep Learning Models

- Many Deep Learning Algorithms like Neural Networks require intense numerical computations
- GPUs can speed up such workloads by parallelizing over many cores
- GPU Computing is a complex topic, so please prepare yourself and set the right expectations. Study the best practise and available mechanisms in your framework of choice to achieve desired speedups and increased computational throughput by leveraging GPUs.

Containerized Multi GPU Computing



Jupyter Lab Notebooks Workflow

Develop and Operationalize your Model with a few simple steps





MLTK Syntax Overview

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

summary <MODEL>

- DLTK Example Syntax
- ... | fit MLTKContainer response from age blood_pressure diabetes_pedigree glucose_concentration mode=stage algo=myalgo epochs=10 batch_size=32 partial_fit=true into app:diabetes_classifier_model



DLTK Syntax Overview

MLTKContainer

• Used as a bridge algorithm, converts data using MLTK's API

Algo

- Defines the Python notebook algorithm & container used as part of the search job
 Mode
- Used to add data into a notebook as a csv, example: mode=stage *Optional*
 Epochs
- "One epoch is when an entire dataset is passed both forward and backward through the **neural network** only once"

Batch_size

• Refers to the number of training examples utilized in one iteration

Partial_fit

 Online learning or "Incremental fit on a batch of samples" used to add <u>incremental updates</u> to a model file as new data is made available

App:

• Describes the model in a shared app context specifies container endpoint to be utilized for a production, more info:

https://docs.splunk.com/Documentation/MLApp/4.4.1/User/Managemodels#Managing_model_permissions_within_Lookups



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Demo





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 side-by-side deployment where the sp 	lunk instance communicates with another instance that is the docker host		Enapoint ORL	localnost			
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single-instance	unix://var/run/docker.sock			yourhostname		linux	
side-by-side	<pre>tcp://remote.host.com:2375</pre>			remote.host.com		any	

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3 diabetes_classifier_model	global	mltk-container-tf-cpu	None	http://localhost:32777	http://localhost:32775	http://localhost:32776
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Example for TensorFlow This example shows a recursive neural network (RNN) fore Make sure to check the information and setup page and pe	cast on univariate data using a long-short i erform all steps needed to run this dashbo	term memory (LSTM) approach. Note that the data has also been scaled us ard successfully.	ing a RobustScaler to ensure that the LSTM forecast converges successfully.
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Use Cases



Splunk customers want answers from their data

Anomaly detection

Predictive Analytics

Clustering



- Advanced Anomaly Detection with Deep Learning Approaches
 - RNN
 - LSTM





- Deep Learning based Regression and Classification
 - Deep Neural Networks
- Sophisticated Predictive Analytics and Time Series Forecasting
 - RNN
 - LSTM

- Deep Learning based approaches
 - Autoencoder
 - Variational Autoencoder



CYBERSECURITY

Anomalous Access Patterns

Goal: Identify entities with deviations from past observations

Long / Short Term Memory (LSTM)

- Plain Language: Finding Users, KPIs or Devices that are acting differently than they have in the past.
- Example: A user authenticates to a higher than normal number of servers using administrative credentials.
- LSTM / RNN neural networks are good <u>for learning</u> the historical and contextual patterns in your data.

"decisions from past iterations or samples can influence current ones"

https://towardsdatascience.com/the-mostly-complete-chart-of-neural-networks-explained-3fb6f2367464



Why RNN/LSTM?

- Basic Idea: LSTM Learns Patterns in the data.
 - Business Rules: Day of Week, Time of Day, & Seasonality
- Model is used to <u>forecast KPI's value</u> the next minute
 - If the actual value is within 1 standard deviation = \sqrt{OK}
 - If the actual value is outside 1 standard deviation = ANOMALY!



https://medium.com/datadriveninvestor/lstm-neural-networks-for-anomaly-detection-4328cb9b6e27



PRODUCTION OPTIMIZATION IN AUTOMOTIVE INDUSTRY

Predictive Maintenance at Volkswagen

- Detect wear of industrial equipment that is used in car assembly lines
- Integration of custom recurrent neural network (RNN) models to detect deviations in operational behavior of industrial equipment
- Visualize results to operators on real time dashboards and generate alerts based on anomaly scores of the RNN models being continously applied to live data







FRAUD

Autoencoder Example

- Goal: Identify transactions with unexpected values or behaviors in the data using reconstruction error
- Plain Language: Finding transactions that are abnormal compared to some set of normal transactions.
- Example: a user transaction request to an unexpected merchant.
- Train an autoencoder to understand how the different features in our data are related to each other.
- "Predict" transaction_amount, merchant_id, account_id, channel, zipcode, etc.

https://www.dataversity.net/fraud-detection-using-a-neural-autoencoder/

https://www.kaggle.com/mlg-ulb/creditcardfraud



Auto Encoder (AE)







Why AutoEncoder?

- Basic Idea: Train model on legitimate transactions
 - Train algorithm to reproduce the feature vectors of each transaction
 - Each feature input, will map to an output value.
 - *n* input variables = *n* output variables
- Model is used to reconstruct transaction x_k
 - Reconstruction Error ε_k is calculated as distance between
 - original x and reproduced \hat{x} transaction.
 - $x_k \rightarrow$ "normal" if $\varepsilon_k \leq K$
 - If the distance between x and \hat{x} is small = \sqrt{OK}
 - $x_k \rightarrow$ "anomaly" if $\varepsilon_k > K$
 - If the distance between x and \hat{x} is above threshold K = FRAUD!
 - Optimize for threshold value K against reconstruction error ε using the validation set





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Wrap up



Key Takeaways Deep Learning Toolkit for Splunk

1. Extend your Splunk platform with the Deep Learning Toolkit for Splunk

2. Integrate custom advanced deep learning and NLP models into Splunk using a predefined Jupyter Notebook workflow for rapid model development.

3. Leverage GPUs for compute intense training tasks



"So how do I get access to this new toolkit?"



Deep Learning Toolkit for Splunk

Download from SplunkBase

- If you're a Splunk admin you can download the DLTK:
- splunkbase.splunk.com/app/4607
- Utilize the install guide
 - Github docs placeholder
- Reach out to Sales & PS for additional support needs
- Splunk Answers

Consult Professional Services

- Machine Learning & Analytics Workshop is a paid offering where Splunk's expert consultants help you:
 - Configuration of Splunk Enterprise, MLTK
 & DLTK
 - Define use case criteria & key business objectives of the ML use case
 - Prepare your data for machine learning
 - Implement use cases
 - Provide guidance on additional value and use cases based on the customer's data sources



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