

DEV DAY



DEV DAY

MLS 1

Build, Train, and Deploy Your Machine Learning Models

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Amazon Web Services

@julsimon



The machine learning workflow is iterative and complex

Prepare

101011010
010101010
000011110

Collect and
prepare
training data

Build



Choose or build an
ML algorithm

Train & Tune



Set up and manage
environments
for training



Train, debug, and
tune models

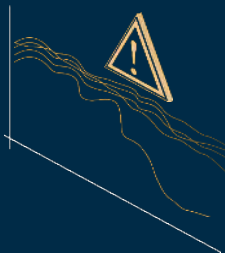


Manage training runs

Deploy & Manage



Deploy
model in
production



Monitor
models



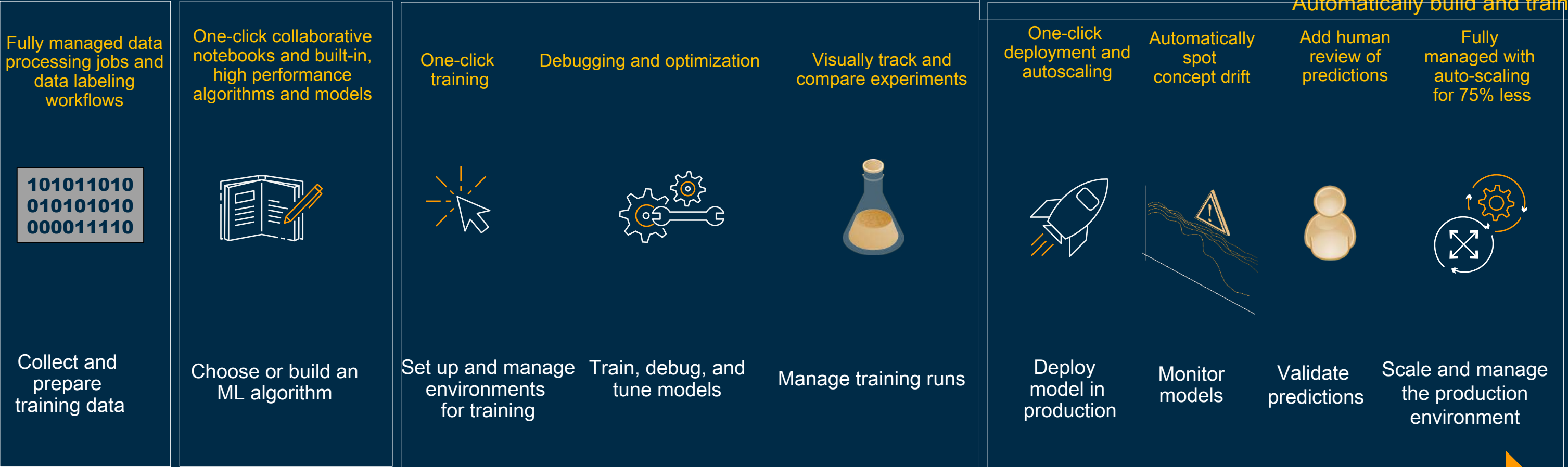
Validate
predictions



Scale and manage
the production
environment



Amazon SageMaker helps you build, train, and deploy models



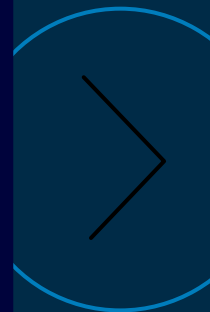
Modular service and APIs, from experimentation to production

DEV DAY

Prepare

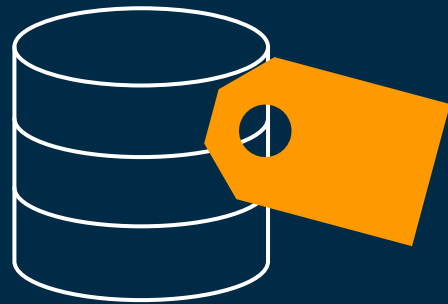


Annotating data at scale is time-consuming and expensive



Amazon SageMaker Ground Truth

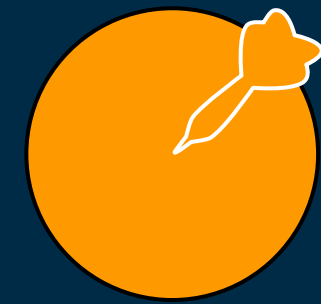
Build scalable and cost-effective labeling workflows



Quickly label
training data



Easily integrate
human labelers



Get accurate
results

KEY FEATURES

Automatic labeling via
machine learning

Ready-made and
custom workflows

Private, 3rd party, and
public workforce



Amazon SageMaker Processing

Analytics jobs for data processing and model evaluation



Fully managed

Achieve distributed processing for clusters



Custom processing

Bring your own script for feature engineering



Container support

Use SageMaker's built-in containers or bring your own



Security and compliance

Leverage SageMaker's security & compliance features



Automatic creation & termination

Your resources are created, configured, & terminated automatically



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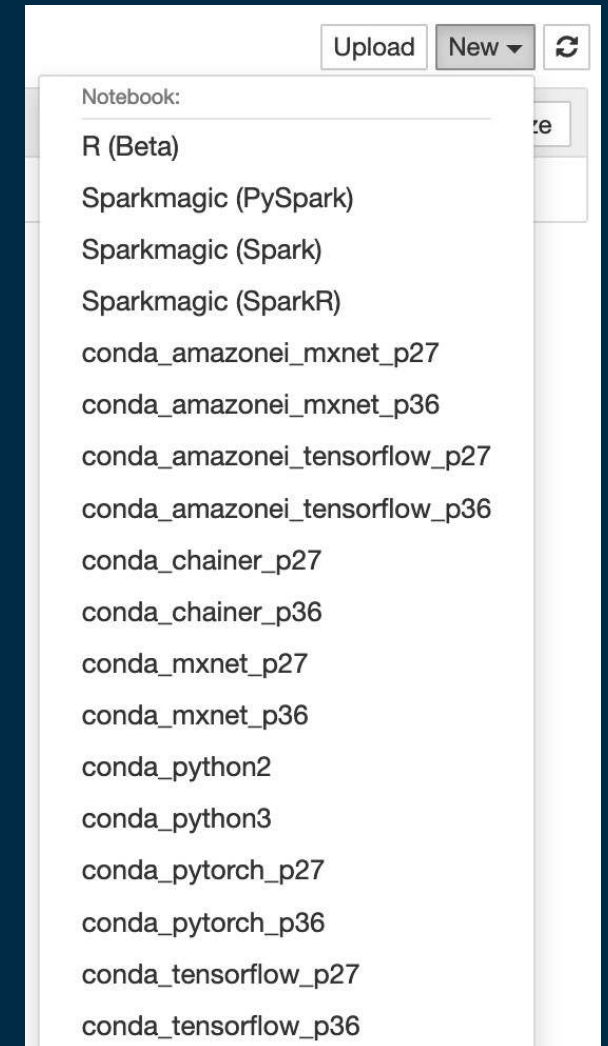
Build



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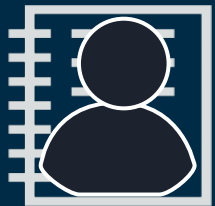
Amazon SageMaker Notebook Instances

- Fully managed instances, from *ml.t2.medium* to *p3.16xlarge*
- Pre-installed with **Jupyter** and **Conda** environments
 - Python 2.7 & 3.6
 - Open-source libraries (TensorFlow, Apache MXNet, etc.)
 - Beta support for R
 - Amazon Elastic Inference for cost-effective GPU acceleration
- Lifecycle configurations
- VPC, encryption, etc.
- Get to work in minutes



Amazon SageMaker Studio

Fully integrated development environment (IDE) for machine learning



Collaboration at
scale

Share notebooks
without tracking code
dependencies



Easy experiment
management

Organize, track, and compare
thousands of experiments



Automatic model
generation

Get accurate models with full
visibility & control without
writing code



Higher quality ML
models

Automatically debug errors,
monitor models, & maintain
high quality



Increased
productivity

Code, build, train, deploy, &
monitor in a unified visual
interface



Amazon SageMaker Studio

Amazon SageMaker Studio File Edit View Run Kernel Git Tabs Settings Help

xgboost_customer_churn.ipynb

conda_amazonei_mxnet_p27

- Have the predictor variable in the first column
- Not have a header row

But first, let's convert our categorical features into numeric features.

```
[ ]: model_data = pd.get_dummies(churn)
      model_data = pd.concat([model_data['Churn?_True'], model_data.drop(['Churn?_True'], axis=1)], axis=1)
```

...

And now let's split the data into training, validation, and test sets. This will help prevent us from overfitting the model, and allow us to test the models accuracy on data it hasn't already seen.

```
[ ]: train_data, validation_data, test_data = np.split(model_data.sample(frac=1, random_state=42), [int(0.33 * len(model_data)), int(0.66 * len(model_data))])
      train_data.to_csv('train.csv', header=False, index=False)
      validation_data.to_csv('validation.csv', header=False, index=False)
```

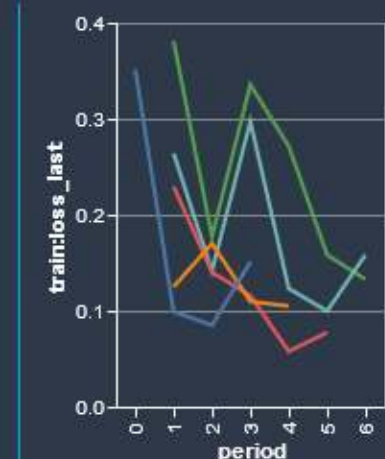
...

Now we'll upload these files to S3.

```
[ ]: boto3.Session().resource('s3').Bucket(bucket).Object(os.path.join(prefix, 'train.csv')).upload_file(train_data.to_csv('train.csv', header=False, index=False))
      boto3.Session().resource('s3').Bucket(bucket).Object(os.path.join(prefix, 'validation.csv')).upload_file(validation_data.to_csv('validation.csv', header=False, index=False))
```

...

Trial Component Chart



Trial Component List

TRIAL COMPONENTS

10 rows selected

Add chart Deploy model

Status	Experiment	Type	Trial	Trial c
✓ Completed	customer-churn-predi...	Training job	Trial-3	Tr
✓ Completed	customer-churn-predi...	Training job	Trial-2	Tr
✓ Completed	customer-churn-predi...	Training job	Trial-1	Tr
✓ Completed	customer-churn-predi...	Training job	Trial-0	Tr

Mode: Command Ln 1, Col 1 xgboost_customer_churn.ipynb

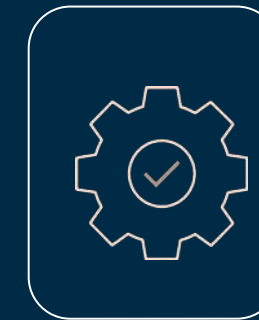
Model options



AWS Marketplace for
Machine Learning



Training code



Amazon SageMaker
AutoPilot

Factorization Machines
Linear Learner
Principal Component
Analysis
K-Means Clustering
Etc.

Built-in Algorithms (17)

No ML coding required



Built-in Frameworks

Bring your own code
Open source containers



Bring Your Own

Full control, run your container
R, C++, etc.

Fully managed training, spot instances included



Built-in algorithms

Orange: supervised, yellow: unsupervised

Linear Learner: Regression, classification	Image Classification: Deep learning (ResNet)
Factorization Machines: Regression, classification, recommendation	Object Detection (SSD): Deep learning (VGG or ResNet)
K-Nearest Neighbors: Non-parametric regression and classification	Neural Topic Model: Topic modeling
XGBoost: Regression, classification, ranking https://github.com/dmlc/xgboost	Latent Dirichlet Allocation: Topic modeling (mostly)
K-Means: Clustering	BlazingText: GPU-based Word2Vec, and text classification
Principal Component Analysis: Dimensionality reduction	Sequence to Sequence: Machine translation, speech to text and more
Random Cut Forest: Anomaly detection	DeepAR: Time-series forecasting (RNN)
Object2Vec: General-purpose embedding	IP Insights: Usage patterns for IP addresses
Semantic Segmentation: Deep learning	



Built-in frameworks: Just add your code



- Built-in containers for **training** and **prediction**
 - Open-source, e.g., <https://github.com/aws/sagemaker-tensorflow-containers>
 - Build them, run them on your own machine, customize them, etc.
- **Local mode**: Train and predict on your **notebook instance**, or on your **local machine**
- **Script mode**: Reuse **existing code** with minimal changes

Amazon SageMaker Autopilot

Automatic model creation with full visibility & control



Quick to start

Provide your data in a tabular form & specify target prediction



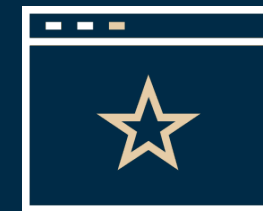
Automatic model creation

Get ML models with feature engineering & model tuning automatically done



Visibility & control

Get notebooks for your models with source code



Recommendations & Optimization

Get a leaderboard & continue to improve your model



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Train & Tune



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The Amazon SageMaker API

- Python SDK **orchestrating** all Amazon SageMaker activity
 - High-level objects for **algorithm selection**, **training**, **deploying**, etc.
<https://github.com/aws/sagemaker-python-sdk>
 - **Spark SDK** (Python & Scala)
<https://github.com/aws/sagemaker-spark/tree/master/sagemaker-spark-sdk>
- AWS SDK
 - Service-level APIs for **scripting** and **automation**
 - CLI: *'aws sagemaker'*
 - Language SDKs: boto3, etc.



Amazon SageMaker Experiments

Organize, track, and compare training experiments



Tracking at scale

Track parameters & metrics across experiments & users



Custom organization

Organize experiments by teams, goals, & hypotheses



Visualization

Easily visualize experiments and compare



Metrics and logging

Log custom metrics using the Python SDK & APIs



Fast Iteration

Quickly go back & forth & maintain high-quality



Amazon SageMaker Automatic Model Tuning

Automatically tune hyperparameters across algorithms



Tuning at scale

Adjust thousands of different combinations of algorithm parameters



Automated

Uses ML to find the best parameters



Faster

Eliminate days or weeks of tedious manual work

Examples

Decision Trees

Tree depth
Max leaf nodes
Gamma
Eta
Lambda
Alpha

Neural Networks

Number of layers
Hidden layer width
Learning rate
Embedding dimensions
Dropout

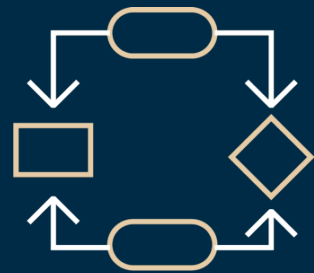
Amazon SageMaker Debugger

Analysis and debugging, explainability, and alert generation



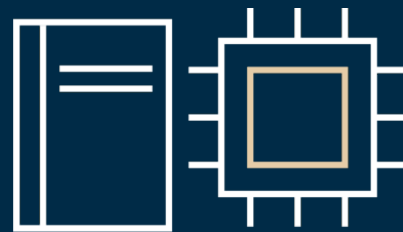
Relevant data
capture

Data is automatically
captured for analysis



Data analysis &
debugging

Analyze & debug data with
no code changes



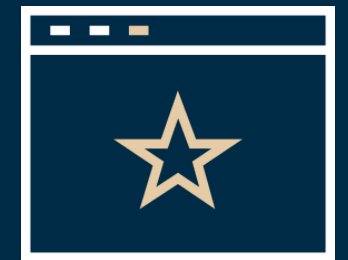
Automatic error
detection

Errors are automatically
detected based on rules



Improved productivity
with alerts

Take corrective action based
on alerts



Visual analysis
and debugging

Visually analyze & debug
from SageMaker Studio



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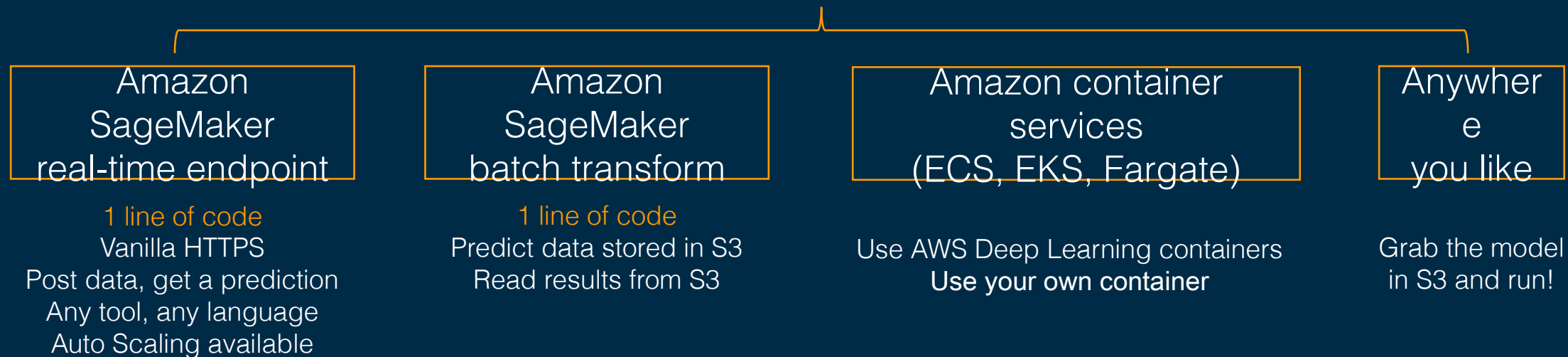
Deploy & Manage



Deployment options



Model in Amazon S3



Fully managed deployment

Amazon SageMaker Model Monitor

Continuous monitoring of models in production



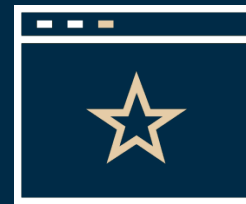
Automatic data
collection

Data is automatically
collected from your
endpoints



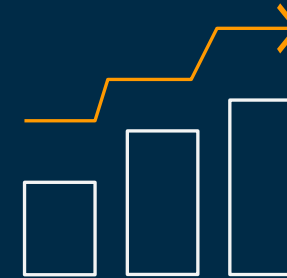
Continuous
Monitoring

Define a monitoring
schedule and detect
changes in quality against
a pre-defined baseline



Flexibility
with rules

Use built-in rules to
detect data drift or write
your own rules for
custom analysis



Visual
data analysis

See monitoring results,
data statistics, and
violation reports in
SageMaker Studio



CloudWatch
Integration

Automate corrective
actions based on Amazon
CloudWatch alerts



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Demo



Getting started

<http://aws.amazon.com/free>

<https://ml.aws>

<https://aws.amazon.com/sagemaker>

<https://github.com/aws/sagemaker-python-sdk>

<https://github.com/aws/sagemaker-spark>

<https://github.com/aws-labs/amazon-sagemaker-examples>

<https://gitlab.com/juliensimon/dlnotebooks>

<https://youtube.com/juliensimonfr>



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Thank you!



Appendix – TensorFlow on SageMaker

TensorFlow

<https://www.tensorflow.org>



- Main API in **Python**, with support for Javascript, Java, C++
- TensorFlow 1.x: **symbolic execution**
 - ‘Define then run’: build a graph, optimize it, feed data, and compute
 - Low-level API: variables, placeholders, tensor operations
 - High-level API: *tf.estimator.**
 - Keras library: *Sequential* and *Functional* API, predefined layers
- TensorFlow 2.0: **imperative execution** (aka eager execution)
 - ‘Define by run’: normal Python code, similar to numpy
 - Run it, inspect it, debug it
 - Keras is the preferred API

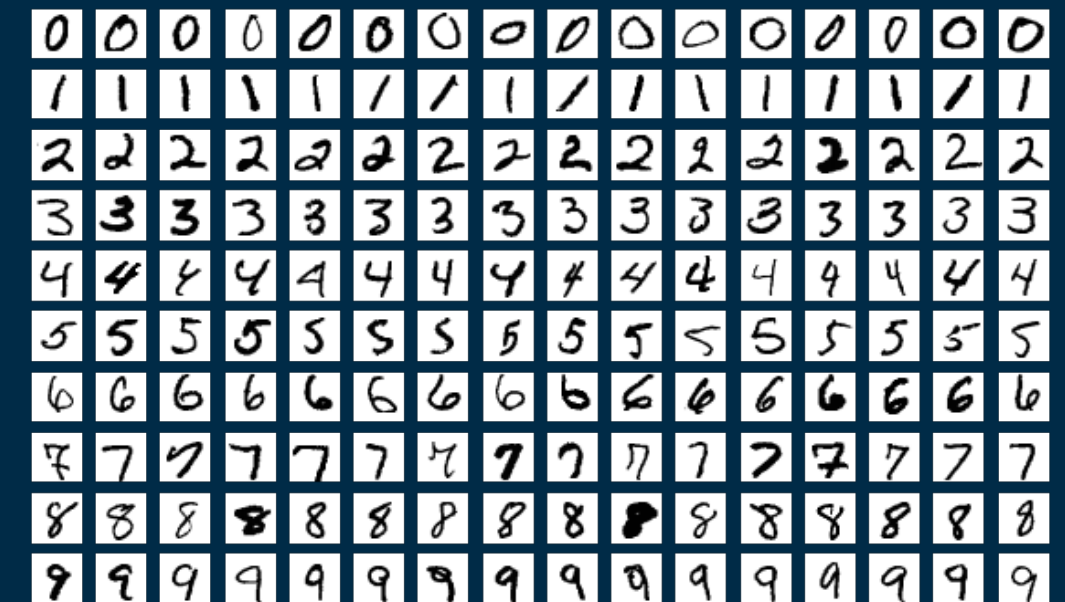
TF1.x: MNIST with a Fully Connected network

```
import tensorflow as tf
mnist = tf.keras.datasets.mnist

(x_train, y_train), (x_test, y_test) = mnist.load_data()
x_train, x_test = x_train / 255.0, x_test / 255.0

model = tf.keras.models.Sequential([
    tf.keras.layers.Flatten(),
    tf.keras.layers.Dense(512, activation=tf.nn.relu),
    tf.keras.layers.Dropout(0.2),
    tf.keras.layers.Dense(10, activation=tf.nn.softmax)
])
model.compile(optimizer='adam',
              loss='sparse_categorical_crossentropy',
              metrics=['accuracy'])

model.fit(x_train, y_train, epochs=5)
model.evaluate(x_test, y_test)
```



AWS: The platform of choice for TensorFlow

<https://aws.amazon.com/tensorflow/>



89% of all deep learning workloads in the cloud run on AWS

85% of all TensorFlow workloads in the cloud run on AWS

Source: Nucleus Research, T147, October 2019



TensorFlow: a first-class citizen on Amazon SageMaker

- Built-in TensorFlow containers for **training** and **prediction**
 - Code available on Github: <https://github.com/aws/sagemaker-tensorflow-containers>
 - Build it, run it on your own machine, customize it, etc.
 - Versions : 1.4.1 → 1.15, 2.0
- Not just TensorFlow
 - **Standard tools**: TensorBoard, TensorFlow Serving
 - **SageMaker features**: Local Mode, Script Mode, Model Tuning, Spot Training, Pipe Mode, Amazon EFS & Amazon FSx for Lustre, Amazon Elastic Inference, etc.
 - **Performance optimizations**: GPUs and CPUs (AWS, Intel MKL-DNN library)
 - **Distributed training**: Parameter Server and Horovod



Training a TensorFlow model

- **Script mode:** simply add your own code.
 - Python 3 required
 - Hyperparameters are passed as command-line arguments
 - Location of training and validation sets are passed as environment variables
 - Location where model must be saved is passed as an environment variable

```
from sagemaker.tensorflow import TensorFlow

tf_estimator = TensorFlow(
    entry_point='my_script.py',
    role=role,
    train_instance_count=1, train_instance_type='ml.p3.2xlarge',
    framework_version='1.15', py_version='py3', script_mode=True,
    hyperparameters={'epochs': 10} )

tf_estimator.fit('s3://bucket/path/to/training/data')
```



Training a TensorFlow model in local mode

- You can train on the notebook instance itself, aka **local mode**.
- This is particularly useful while experimenting:
you can save time and money by not firing up training instances.

```
from sagemaker.tensorflow import TensorFlow

tf_estimator = TensorFlow(
    entry_point='my_script.py',
    role=role,
    train_instance_count=1, train_instance_type='local',    # or 'local_gpu'
    framework_version='1.15', py_version='py3', script_mode=True,
    hyperparameters={'epochs': 10} )

tf_estimator.fit('file://path/to/training/data')
```

Training a TensorFlow model on multiple instances

- Aka **Distributed Training**
- Parameter Server (native mode), or Horovod
- Amazon SageMaker takes care of all infrastructure setup.

```
from sagemaker.tensorflow import TensorFlow

tf_estimator = TensorFlow(
    entry_point='my_script.py',
    role=role,
    train_instance_count=8, train_instance_type='ml.p3.2xlarge',
    framework_version='1.15', py_version='py3', script_mode=True,
    hyperparameters={'epochs': 10} )

tf_estimator.fit('s3://bucket/path/to/training/data')
```


Training on infinitely large data sets with Pipe Mode

- By default, Amazon SageMaker copies the data set to all training instances.
 - This is the best option when the data set fits in memory.
- For larger data sets, **Pipe Mode** lets you stream data from Amazon S3.
 - Training starts faster.
 - You can train on infinitely large data sets.

```
from sagemaker.tensorflow import TensorFlow

tf_estimator = TensorFlow(
    entry_point='my_script.py',
    role=role,
    train_instance_count=1, train_instance_type='ml.p3.2xlarge',
    framework_version='1.15', py_version='py3', script_mode=True,
    input_mode='Pipe'
)

tf_estimator.fit('s3://bucket/path/to/training/data')
```



Streaming *TfRecord* files with Pipe Mode

```
from sagemaker_tensorflow import PipeModeDataset
```

```
features = { 'data': tf.FixedLenFeature([], tf.string),  
             'labels': tf.FixedLenFeature([], tf.int64)}
```

```
def parse(record):  
    parsed = tf.parse_single_example(record, features)  
    return ({ 'data': tf.decode_raw(parsed['data'], tf.float64) }, parsed['labels'])
```

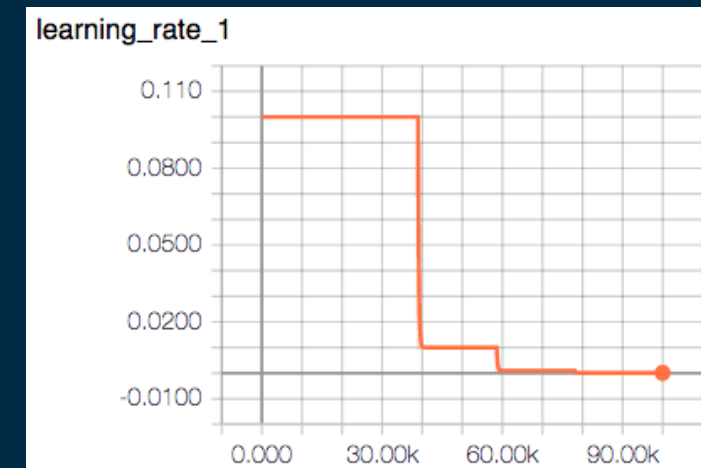
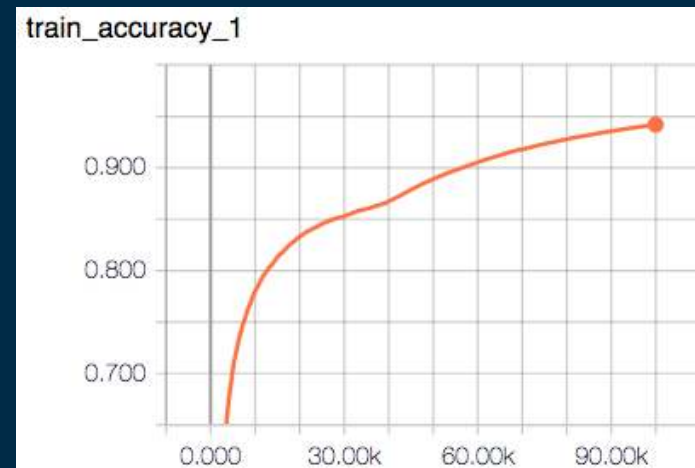
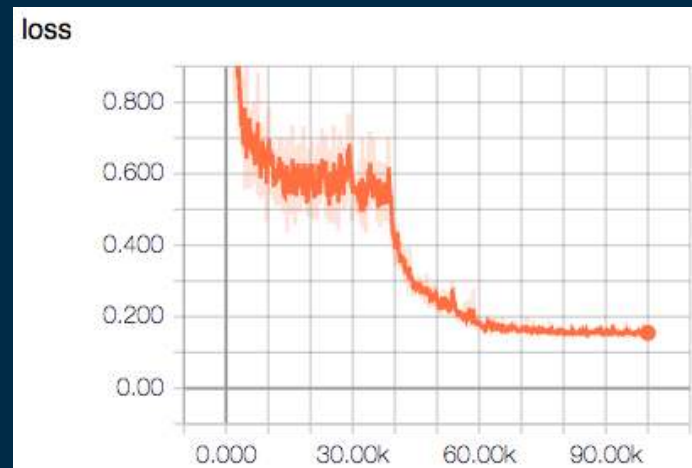
```
def train_input_fn(training_dir, hyperparameters):  
    ds = PipeModeDataset(channel='training', record_format='TFRecord')  
    ds = ds.repeat(20)  
    ds = ds.prefetch(10)  
    ds = ds.map(parse, num_parallel_calls=10)  
    ds = ds.batch(64)  
    return ds
```



Visualizing training with TensorBoard

- TensorBoard is a suite of visualization tools: graph, metrics, etc.
- When enabled, it will run on the notebook instance.
- You can access it at https://NOTEBOOK_INSTANCE/proxy/6006/

```
tf_estimator.fit(inputs, run_tensorboard_locally=True)
```



Deploying a TensorFlow model to an HTTPS endpoint

Model trained on-demand

```
from sagemaker.tensorflow import TensorFlow

tf_estimator = TensorFlow(entry_point='tf-train.py', ...)
tf_estimator.fit(inputs)

predictor = tf_estimator.deploy(initial_instance_count=1, instance_type='ml.c4.xlarge')
```

Pretrained Model

```
from sagemaker.tensorflow import TensorFlowModel

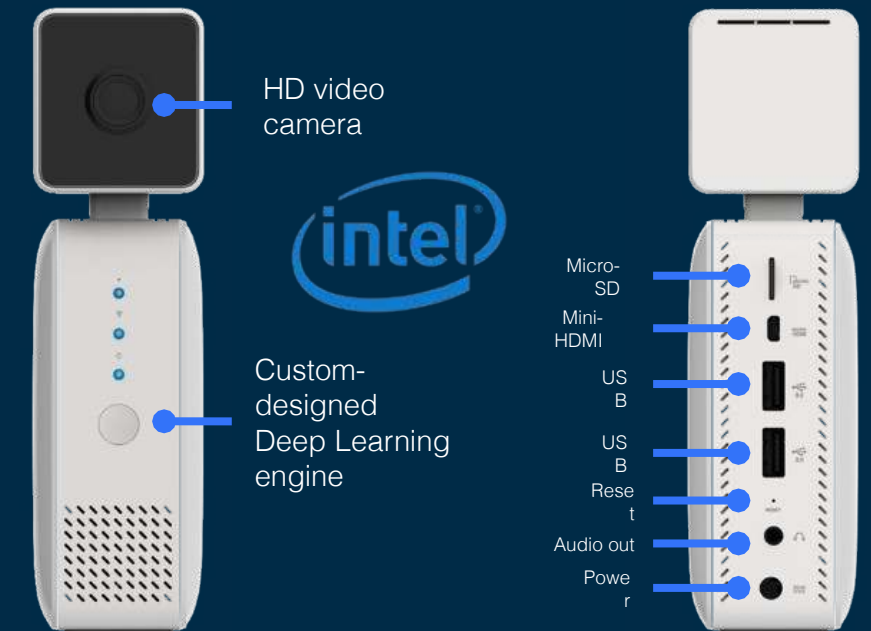
tf_model = TensorFlowModel(model_data='s3://mybucket/model.tar.gz', ...,
                           entry_point='entry.py', name='model_name')

predictor = tf_model.deploy(initial_instance_count=1, instance_type='ml.c4.xlarge')
```



Using TensorFlow with AWS DeepLens

- AWS DeepLens can run TensorFlow models.
 - Inception
 - MobileNet
 - NasNet
 - ResNet
 - VGG
- Train or fine-tune your model on Amazon SageMaker.
- Deploy to DeepLens through AWS Greengrass.



Getting started

<http://aws.amazon.com/free>

<https://aws.amazon.com/tensorflow/>

<https://aws.amazon.com/sagemaker>

<https://github.com/aws/sagemaker-python-sdk>

https://sagemaker.readthedocs.io/en/stable/using_tf.html

<https://github.com/aws-labs/amazon-sagemaker-examples>

<https://gitlab.com/juliensimon/aim410> End to end demo with Keras & SageMaker

