BlueVine

DATASCIENCEGO
Conference 2019

Deploying ML Models from Scratch

Ido Shlomo - Senior Data Science Manager

BlueVine

About BlueVine

- Fintech startup up based in Redwood City, CA
- Provides working capital (loans) to small & medium sized businesses
- Over $2 BN funded to date
- Data Science challenges:
  - Consume many different semi structured / unstructured data sources
  - Deal with noisy / weak signals
  - Make decisions fast
  - Build models that are stable and accurate

About Me

- Data Science Manager @ BlueVine
- Lead BlueVine's DS team in Redwood City, CA (total of ~20 people across RWC & TLV)
- Team focus:
  - NLP & text mining
  - Anomaly detection
  - Probabilistic ML
  - Response modeling
- Personal interests: Unstructured data and DS Infrastructure.

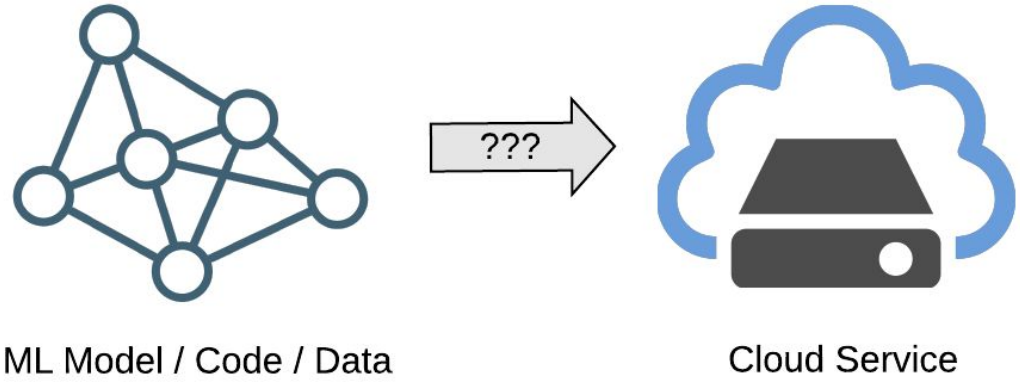
Code & Slides

- Git Repo: https://github.com/ido-sh
- Slides:
- Code:

The Issue

- In a Business context:
  Be able to "deliver" something

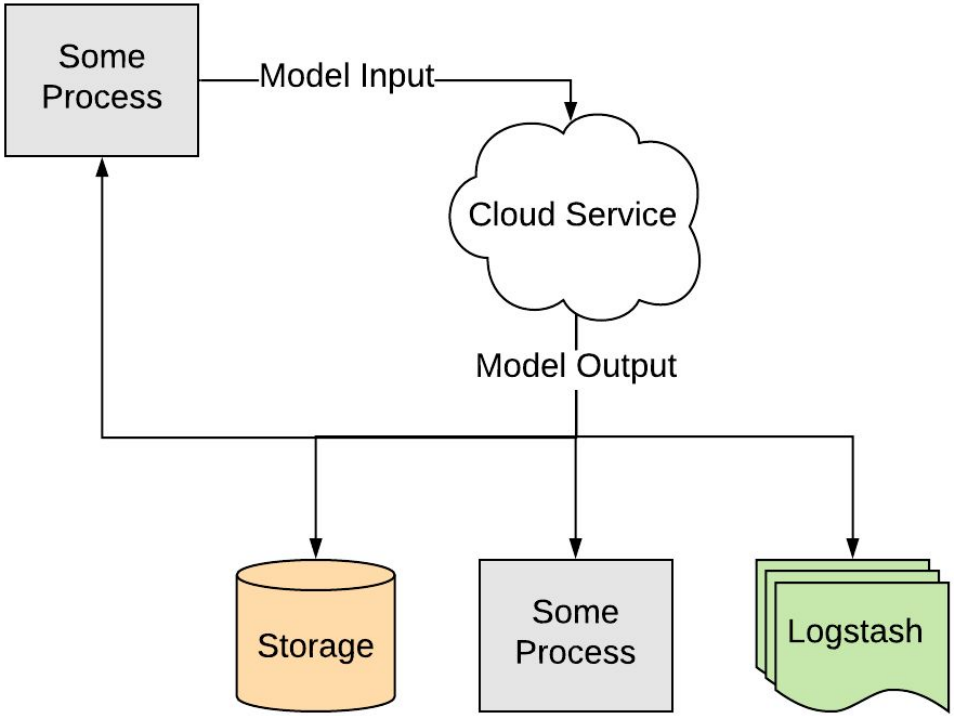
- In Research context:
  Free it from constraints of a local machine



The Desired End Result

Cloud Service:

- Model hosted in the cloud
- Always up (persistence)
- Communicates via API
- Can scale



The Starting Point

Desired Solution

Something that deploys our code as a cloud service

AND

In way that is:

- **Flexible**: Handle any type of Python code or structure
- **Simple**: Requires minimal effort to run
- **Independent**: Can run end-to-end by a Data Scientist with normal skill-set

Some leading deployment paradigms

Solution	Example Setups	Problem
Hand off everything to a team of Engineers	● Data Scientist sends to Engineer: ○ Code & binaries ○ Environment & tests ○ Deployment config ● Engineer: ○ Rewrites code ○ Checks tests ○ Deploys (somehow)	**Not independent**

Some leading deployment paradigms

Solution	Example Setups	Problem
Jointly manage deployment environment with Engineers	● Data Scientist: ○ Pushes code & binaries to repo / storage ○ Adheres to preset deployment config (environment, tests) ● Engineer: ○ QA for code repo / storage ○ Deploys (somehow)	**Semi-independent, Semi-flexible**

Some leading deployment paradigms

Solution	Example Setups	Problem
Develop on a fully managed deployment-capable platform	● DataRobot ● Alteryx ● ML-Flow ● Many others...	**Not flexible**

Some leading deployment paradigms

Solution	Example Setups	Problem
Build your own docker containers and deploy them	● Docker to bundle code and build containers ● A Docker registry to store them ● A Docker orchestration tool to deploy them: ○ Kubernetes ○ Docker Swarm ○ Mesos ○ Many others...	**Not simple**

Amazon SageMaker

Motivation: Get all the pros of docker deployment without writing any docker code

- **Flexible**: Can work with any custom Python code, environment & data files
- **Simple**: Requires relatively basic Python code to run
- **Independent**: Can build docker containers and deploy them, both for cloud training jobs and deployment of cloud services

Supports four modes: Tag, Explore, **Train** and **Deploy**

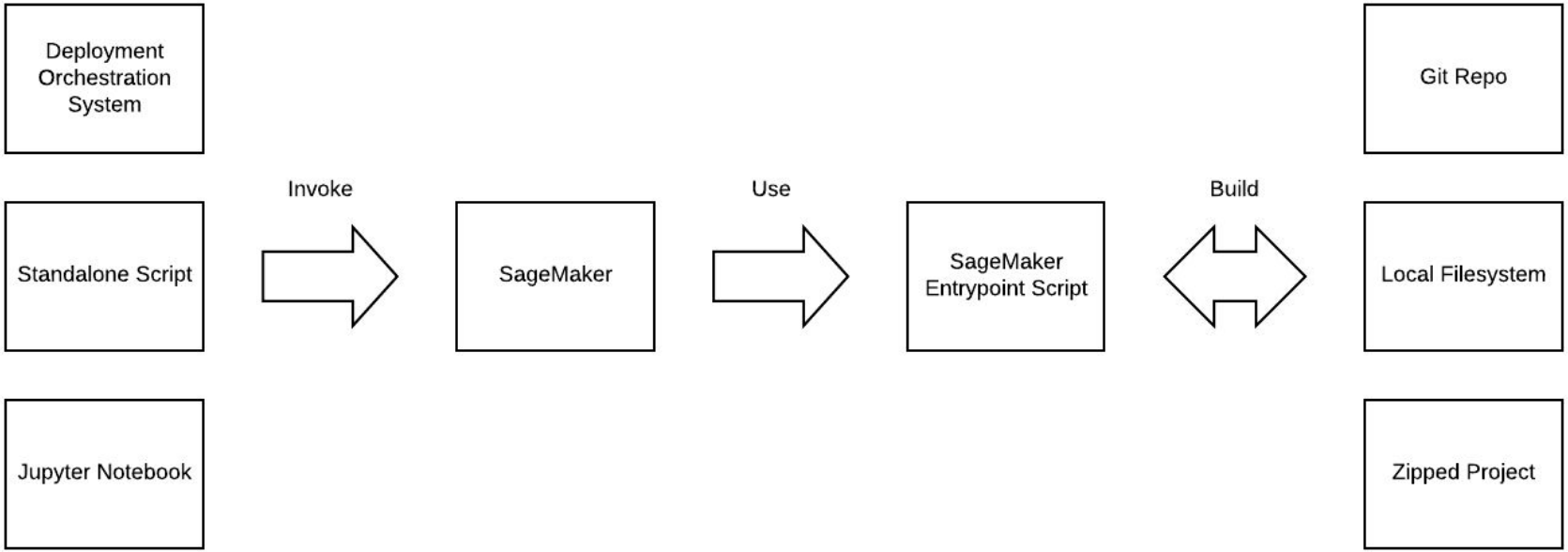
Amazon SageMaker

We're turning **ALL** of our main Data Science deliverables into cloud services

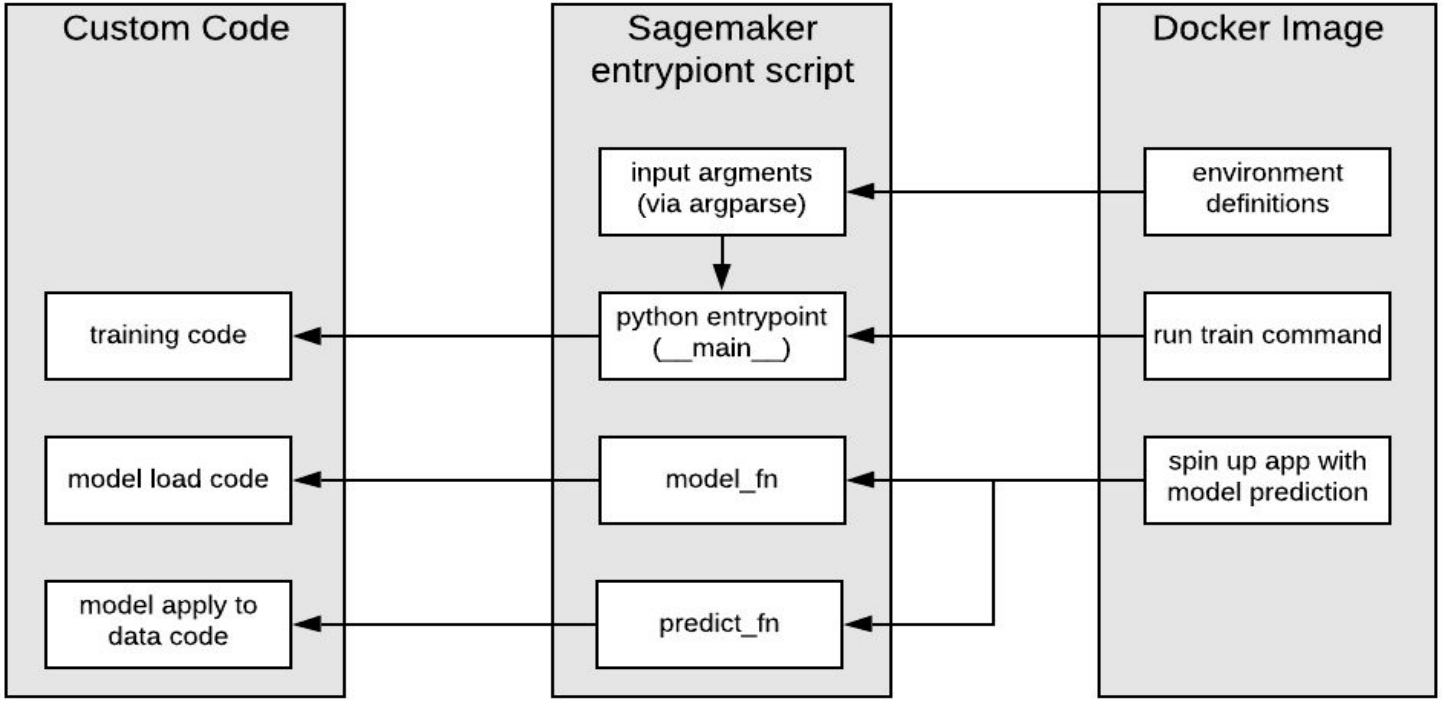
Some notable examples:

- Client Risk score
- Client Fraud score
- Industry classification
- Insights from external sources:
    - Bank data
    - Credit report data
    - Government filing data

Project Structure



Internal Connections



Example > entrypoint.py

```
import custom_code  # importing whatever custom code you have

# THIS HANDLES TRAINING (DEFAULT SCRIPT INVOKE)
if __name__ == '__main__': ...


# THIS LOADS A TRAINED MODEL
def model_fn(model_dir): ...


# THIS APPLIES MODEL TO INPUT AND RETURNS PREDICTION
def predict_fn(input_data, model): ...
```

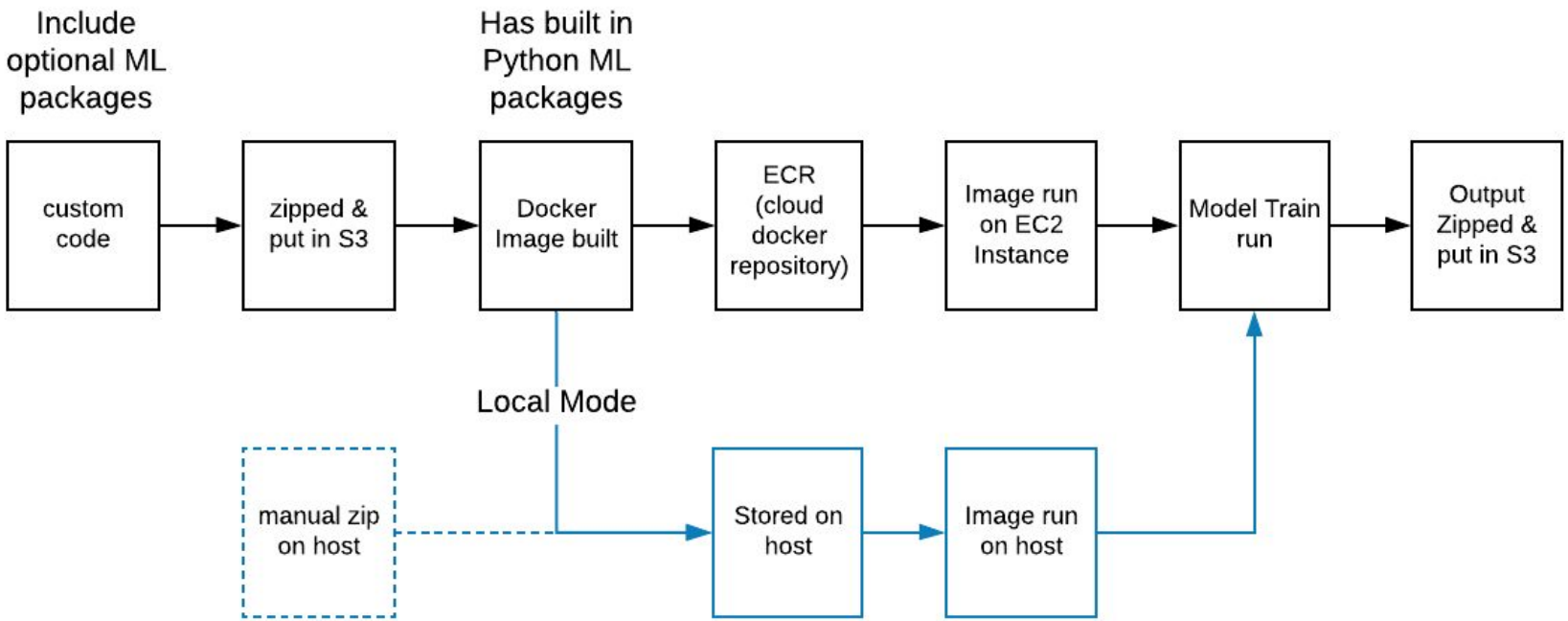
Example > entrypoint.py > __main__

```
# THIS HANDLES TRAINING (DEFAULT SCRIPT INVOKE)
if __name__ == '__main__':

    # parse environment variables
    parser = argparse.ArgumentParser()
    parser.add_argument('--output-data-dir', type=str, default=os.environ['SM_OUTPUT_DATA_DIR'])
    parser.add_argument('--model-dir', type=str, default=os.environ['SM_MODEL_DIR'])
    parser.add_argument('--train', type=str, default=os.environ['SM_CHANNEL_TRAIN'])
    args = parser.parse_args()

    # read training data from train directory
    input_files = [os.path.join(args.train, file) for file in os.listdir(args.train)]
    raw_data = [pd.read_csv(file) for file in input_files]
    train_data = pd.concat(raw_data)

    # fit model to data
    name_comparison_model = custom_code.fit_model(train_data)

    # save model as file
    custom_code.save_model(name_comparison_model, args.model_dir)
```

Example > entrypoint.py > model_fn / input_fn / predict_fn

```python
# THIS LOADS A TRAINED MODEL
def model_fn(model_dir):
    mdl = custom_code.load_model(model_dir)
    return mdl


# THIS APPLIES MODEL TO INPUT AND RETURNS PREDICTION
def predict_fn(input_data, model):
    mdl_output = custom_code.use_model(input_data, model)
    return mdl_output
```

Train Run


Include optional ML packages
Has built in Python ML packages
custom code
zipped & put in S3
Docker Image built
ECR (cloud docker repository)
Image run on EC2 Instance
Model Train run
Output Zipped & put in S3
Local Mode
manual zip on host
Stored on host
Image run on host

Train Run

In [1]:
```
import sagemaker
from boto3 import Session as BotoSession
from time import sleep

# create sagemaker session
boto_session = BotoSession(profile_name='default',
                           region_name='us-east-1')
sagemaker_session = sagemaker.Session(boto_session=boto_session)
sagemaker_role = 'ido-sagemaker-test'
```

Train Run

In [2]:
```
#  upload training data to s3
train_dir = 'data/train'
project_name = 'sagemaker-dsgo-tutorial'
train_input = sagemaker_session.upload_data(
    train_dir, key_prefix="{}/{}".format(project_name, train_dir))
print('location in s3: {}'.format(train_input))
```

```
location in s3: s3://sagemaker-us-east-1-[redacted]/sagemaker-dsgo-tuto
rial/data/train
```

Train Run

In [3]:
```
from sagemaker.sklearn.estimator import SKLearn

# config model training
cloud_model = SKLearn(
    entry_point='sagemaker_entry_point.py',
    source_dir='.',
    train_instance_type='ml.c4.xlarge',
    train_instance_count=1,
    role=sagemaker_role
)
```

Train Run

```
In [4]: # run model training (data has to be from s3)
        cloud_model.fit({'train': train_input})
```

```
Training Env:

{
    "input_config_dir": "/opt/ml/input/config",
    "job_name": "sagemaker-scikit-learn-[redacted]",
    "module_dir": "s3://sagemaker-us-east-[redacted]/sagemaker-scikit
-learn-[redacted]/source/sourcedir.tar.gz",
    "user_entry_point": "sagemaker_entry_point.py",
    "is_master": true,
    "input_dir": "/opt/ml/input",
    "log_level": 20,
    "input_data_config": {
        "train": {
            "S3DistributionType": "FullyReplicated",
            "RecordWrapperType": "None",
            "TrainingInputMode": "File"
        }
    },
    "output_dir": "/opt/ml/output",
```

aws Services Resource Groups N. Virginia Support

Search

- Ground Truth
  - Labeling jobs
  - Labeling datasets
  - Labeling workforces
- Notebook
  - Notebook instances
  - Lifecycle configurations
  - Git repositories
- Training
  - Algorithms
  - Training jobs
  - Hyperparameter tuning jobs
- Inference
  - Compilation jobs
  - Model packages
  - Models
  - Endpoint configurations
  - Endpoints
  - Batch transform jobs

Training Panel

Amazon SageMaker > Training jobs

Training jobs

Actions | Create training job

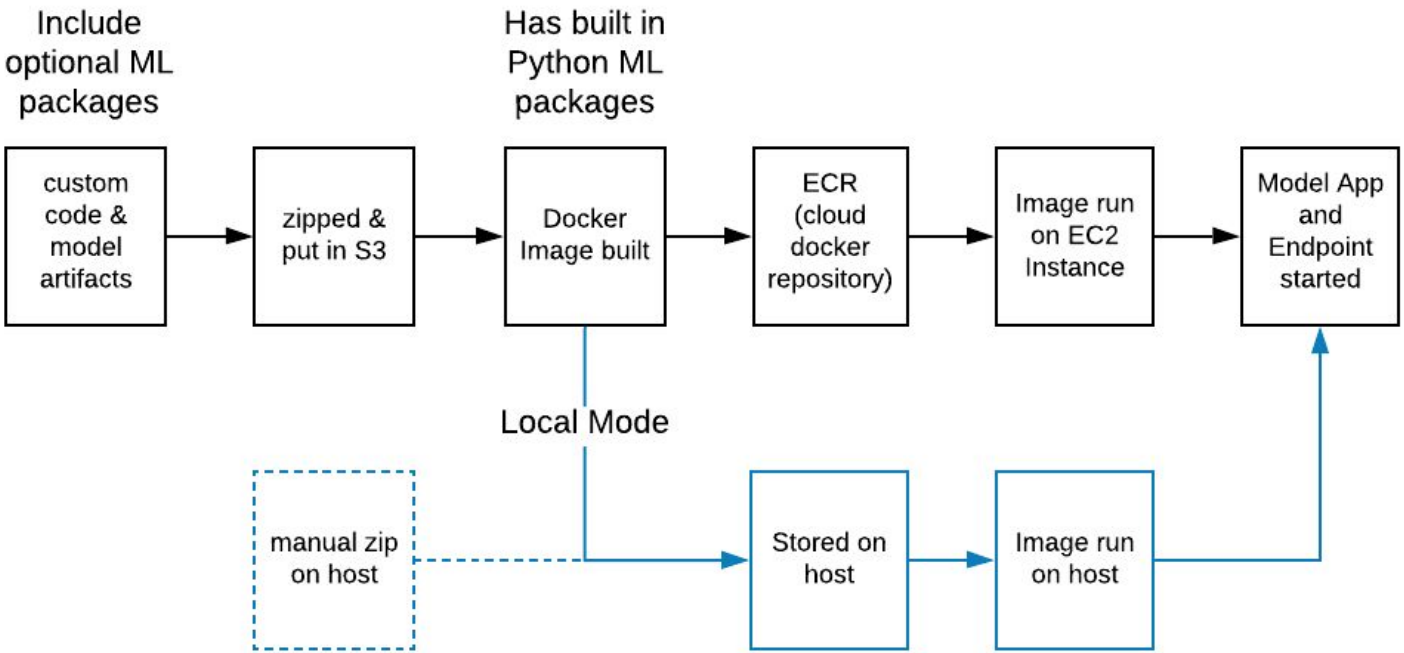
Search training jobs

Training Jobs Panel

1

Name	Creation time	Duration	Status
sagemaker-scikit-learn-	Sep 20, 2019 19:19 UTC	3 minutes	Completed
sagemaker-scikit-learn-	Sep 20, 2019 01:28 UTC	3 minutes	Completed
sagemaker-scikit-learn-	Sep 20, 2019 00:40 UTC	3 minutes	Completed
sagemaker-scikit-learn-	Sep 20, 2019 00:31 UTC	3 minutes	Completed
sagemaker-scikit-learn-	Sep 20, 2019 00:05 UTC	4 minutes	Failed
sagemaker-scikit-learn-	Sep 19, 2019 23:51 UTC	3 minutes	Failed
sagemaker-scikit-learn-	Sep 10, 2019 00:22 UTC	8 minutes	Completed
sagemaker-scikit-learn-	Sep 10, 2019 00:13 UTC	3 minutes	Completed

Deploy Run


Include optional ML packages
Has built in Python ML packages
custom code & model artifacts
zipped & put in S3
Docker Image built
ECR (cloud docker repository)
Image run on EC2 Instance
Model App and Endpoint started
Local Mode
manual zip on host
Stored on host
Image run on host

Deploy Run

In [7]:
```
# from model trained on cloud via sagemaker
cloud_predictor = cloud_model.deploy(initial_instance_count=1,
                                     instance_type="ml.m4.xlarge")
```

```
-----------------------------------------------------------------------
------------------------!
```

aws Services Resource Groups N. Virginia Support

- Ground Truth
  - Labeling jobs
  - Labeling datasets
  - Labeling workforces
- Notebook
  - Notebook instances
  - Lifecycle configurations
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- Training
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  - Endpoint configurations
  - Endpoints
  - Batch transform jobs

Amazon SageMaker > Endpoints

Endpoints

Update endpoint | Actions | Create endpoint

Search endpoints

1

Endpoints Panel

	Name	ARN	Creation time	Status	Last updated
○	debtor-model	[redacted]/debtor-model	Jul 07, 2019 11:03 UTC	InService	Sep 11, 2019 03:46 UTC
○	ido-sagemaker-test5	[redacted]/ido-sagemaker-test5	Jul 01, 2019 22:02 UTC	InService	Sep 11, 2019 21:55 UTC
○	ido-sagemaker-test4	[redacted]/ido-sagemaker-test4	Jul 01, 2019 18:53 UTC	Failed	Jul 01, 2019 19:05 UTC
○	ido-sagemaker-test	[redacted]/ido-sagemaker-test	Jun 30, 2019 18:35 UTC	Failed	Jun 30, 2019 18:35 UTC
○	ido-sagemaker-test3	[redacted]/ido-sagemaker-test3	Jun 30, 2019 18:16 UTC	Failed	Jun 30, 2019 18:21 UTC

Deployment Panel

Other Train / Deploy modes

Local Mode

- Uses docker on local machine instead of on EC2 instance in the cloud
- Train: Trained on local machine
- Deploy: Deploy an endpoint on local machine
- Does **NOT** mean offline
- Useful for debugging (avoids spin up latency & cloud computing costs)

External Model Deployment: Run deployment cycle using model trained outside SageMaker.

[Additional code examples in my repo]

Conclusion

Key Takeaways:

- To make your models “actionable”, you need to be able to deploy them
- Having a flexible, simple and independent deployment mechanism is hugely empowering
- Amazon SageMaker is one such mechanism

Some SageMaker caveats:

- Not the easiest to debug
- Local mode is not 100% offline
- Vendor lock in (Amazon)

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Questions? + Thanks!

ido.shlomo@bluevine.com