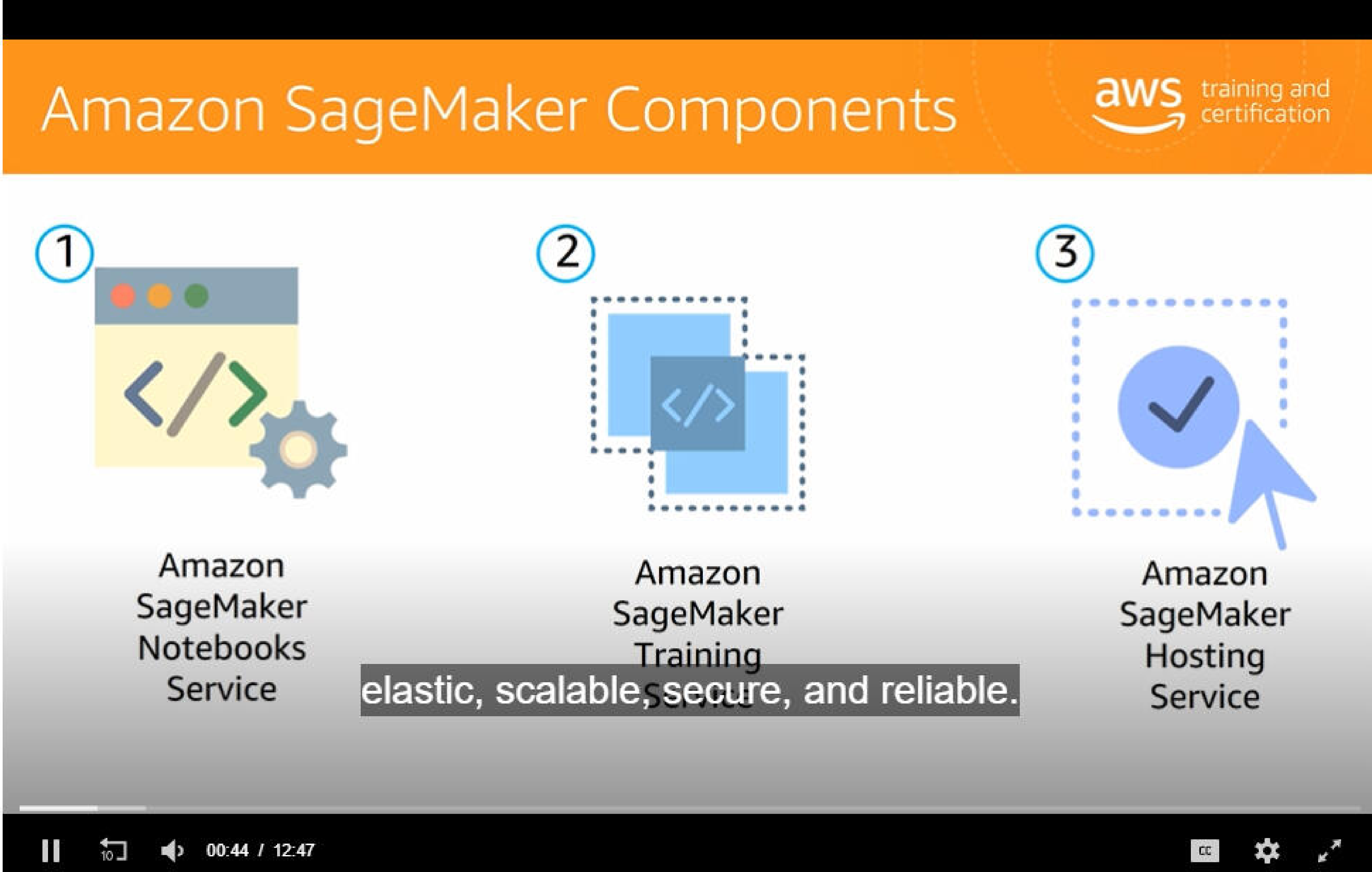

Amazon SageMaker Components
aws training and certification
1
Amazon SageMaker Notebooks Service
2
Amazon SageMaker Training Service
3
Amazon SageMaker Hosting Service
elastic, scalable, secure, and reliable.
00:44 / 12:47

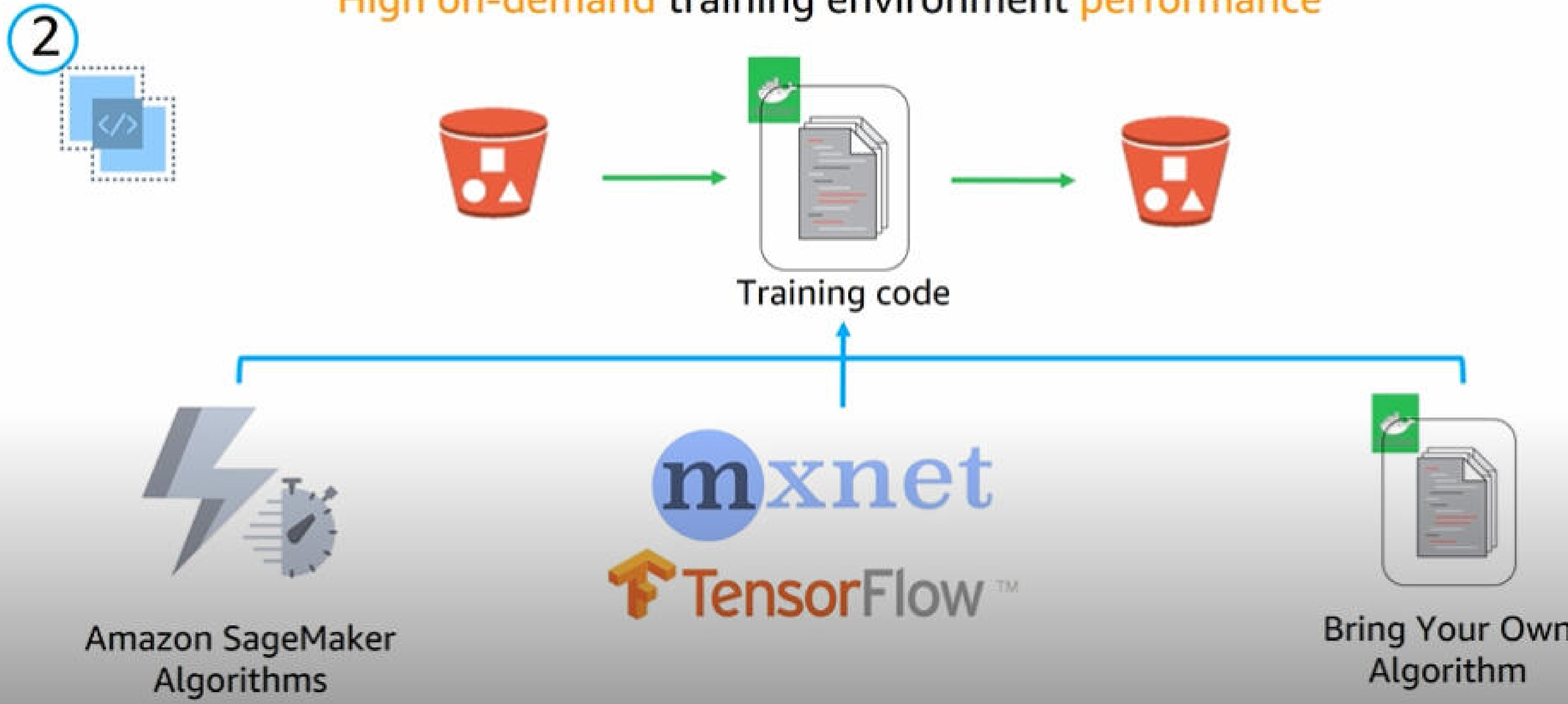
Zero Setup for Exploratory Data Analysis

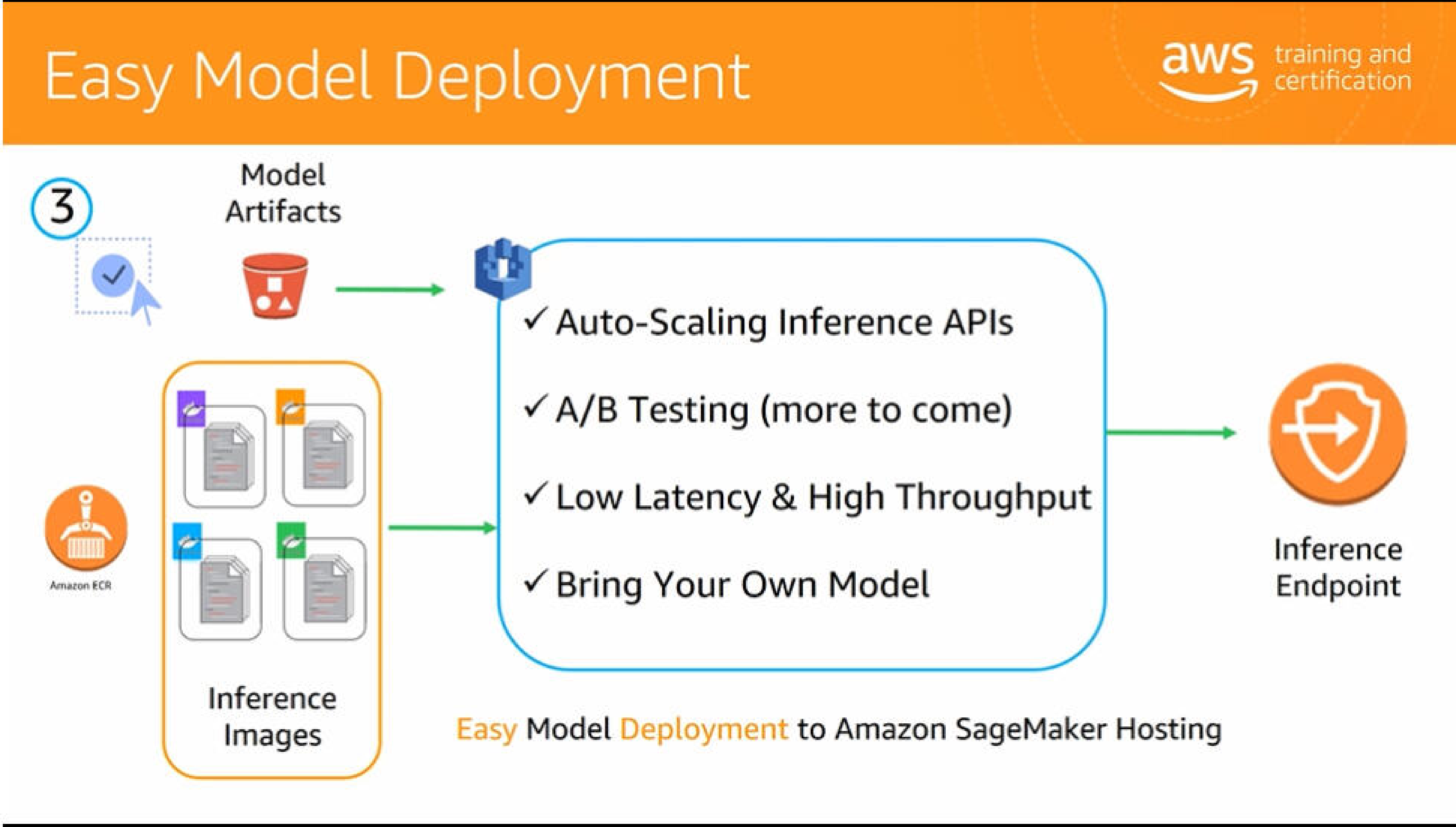
aws training and certification

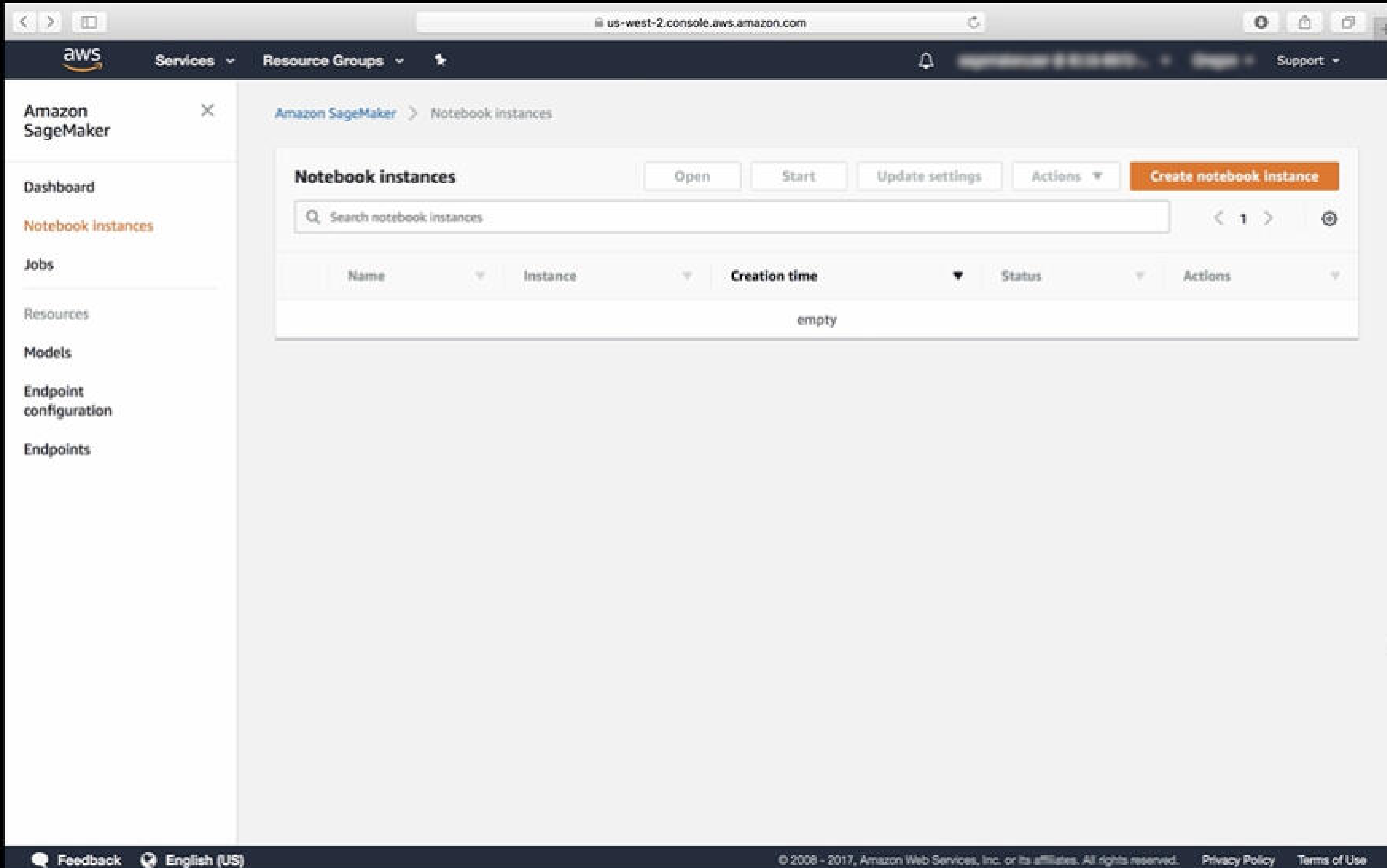
01:04 / 12:47

High Performance, On-Demand

High on-demand training environment performance




Easy Model Deployment
aws training and certification
3
Model Artifacts
✓ Auto-Scaling Inference APIs
✓ A/B Testing (more to come)
✓ Low Latency & High Throughput
✓ Bring Your Own Model
Amazon ECR
Inference Images
Inference Endpoint
Easy Model Deployment to Amazon SageMaker Hosting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Update settings
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Search notebook instances
1
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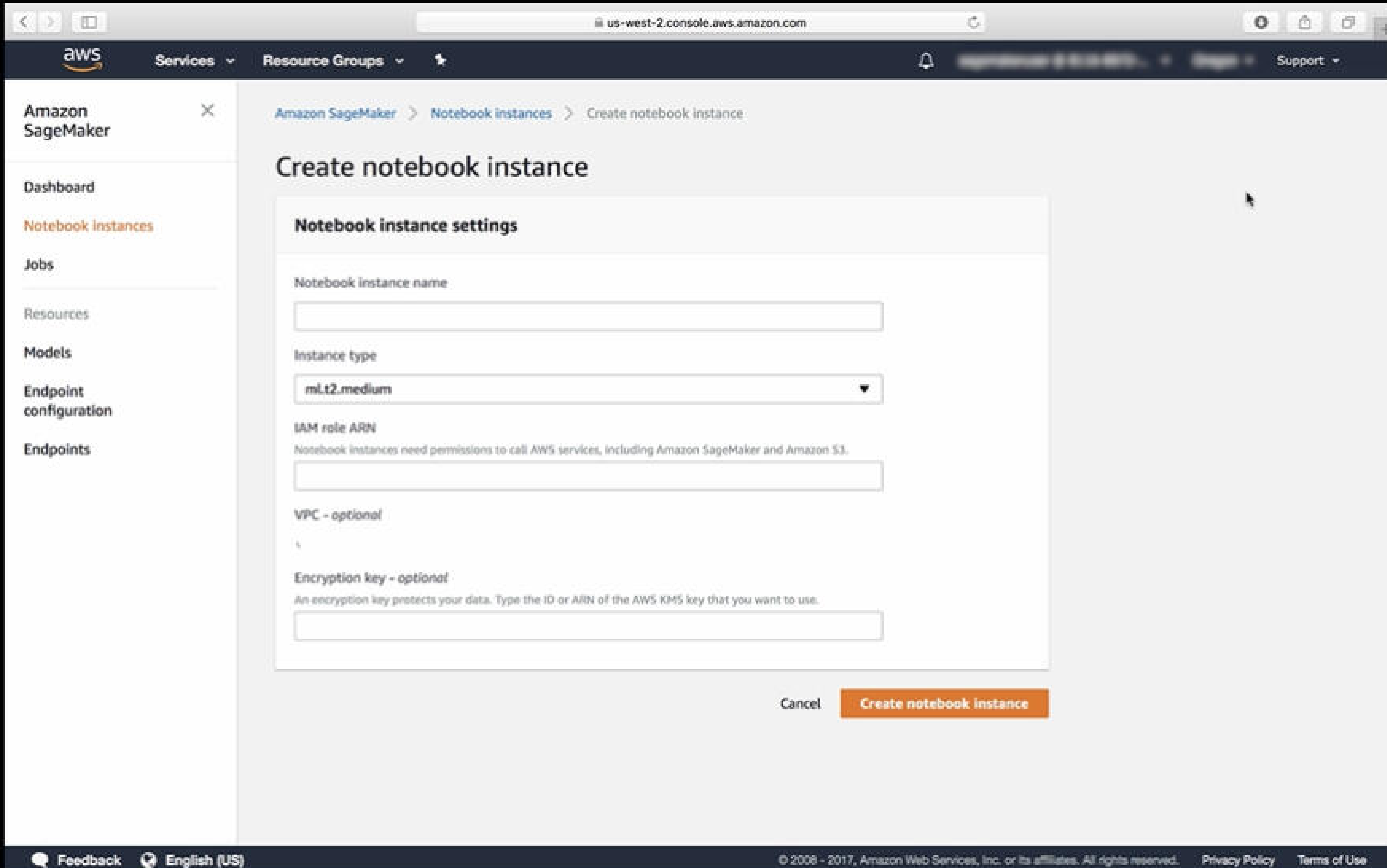
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Create notebook instance
Notebook instance settings
Notebook instance name
Instance type
ml.t2.medium
IAM role ARN
Notebook instances need permissions to call AWS services, including Amazon SageMaker and Amazon S3.
VPC - optional
Encryption key - optional
An encryption key protects your data. Type the ID or ARN of the AWS KMS key that you want to use.
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English (US)
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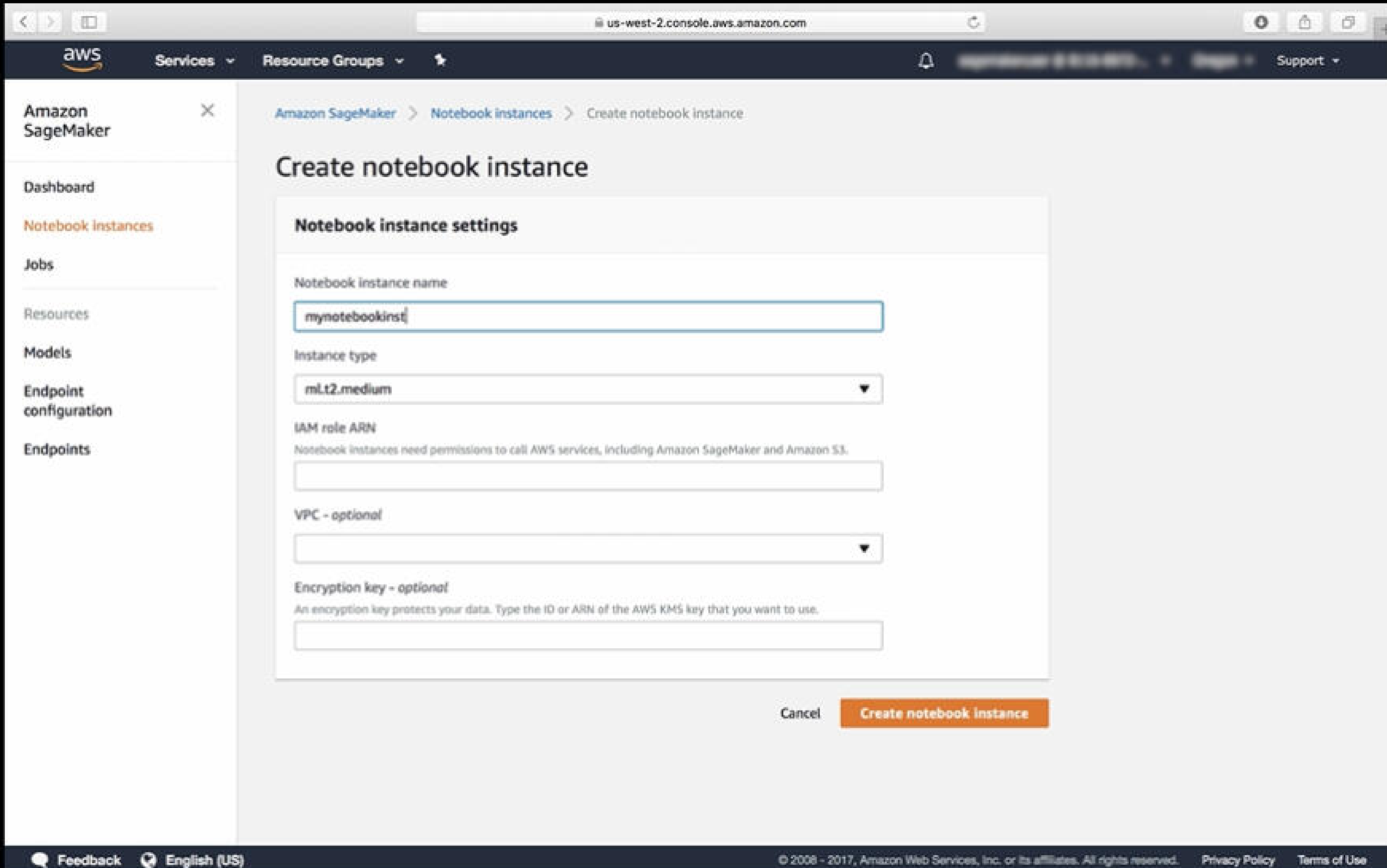
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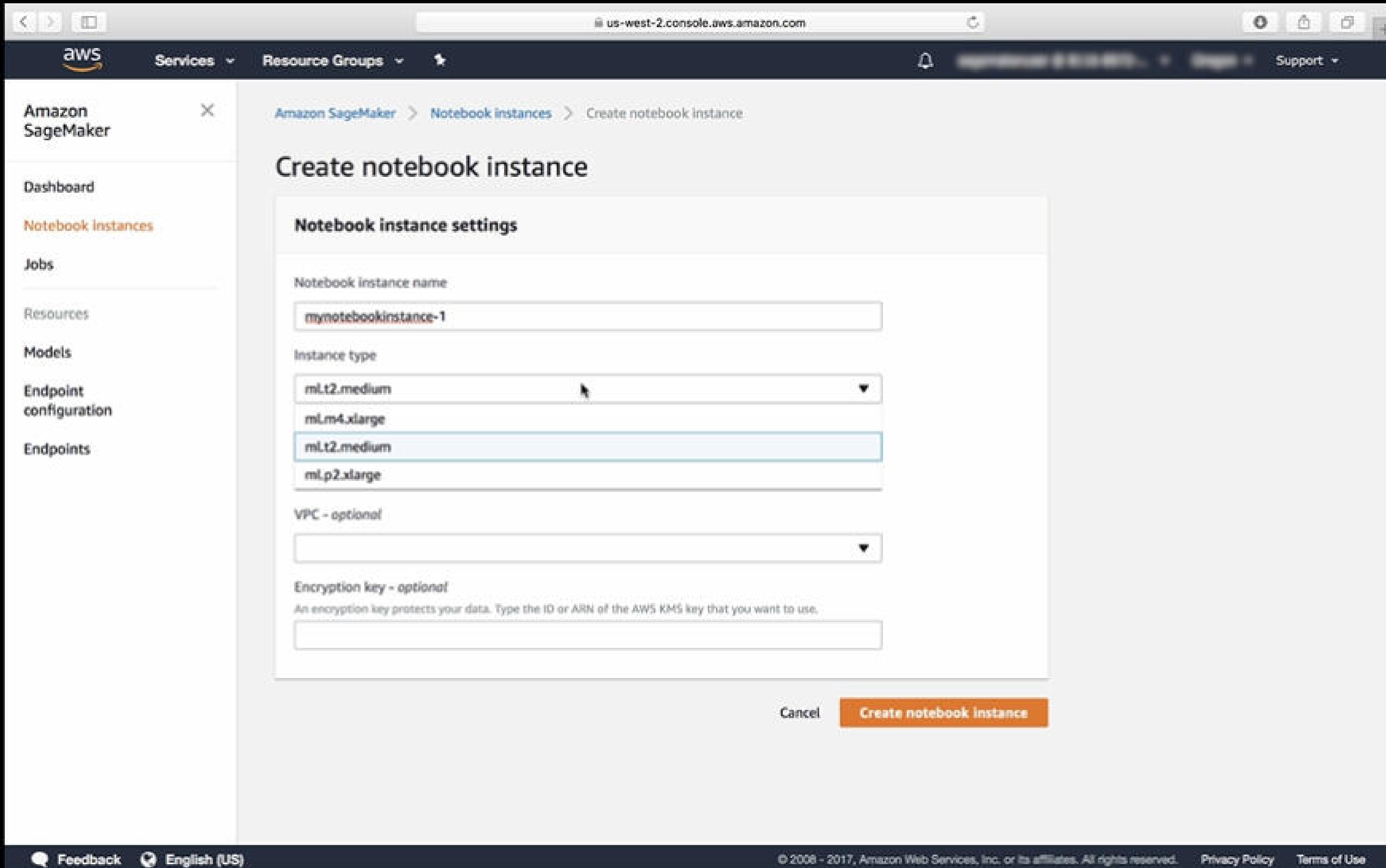
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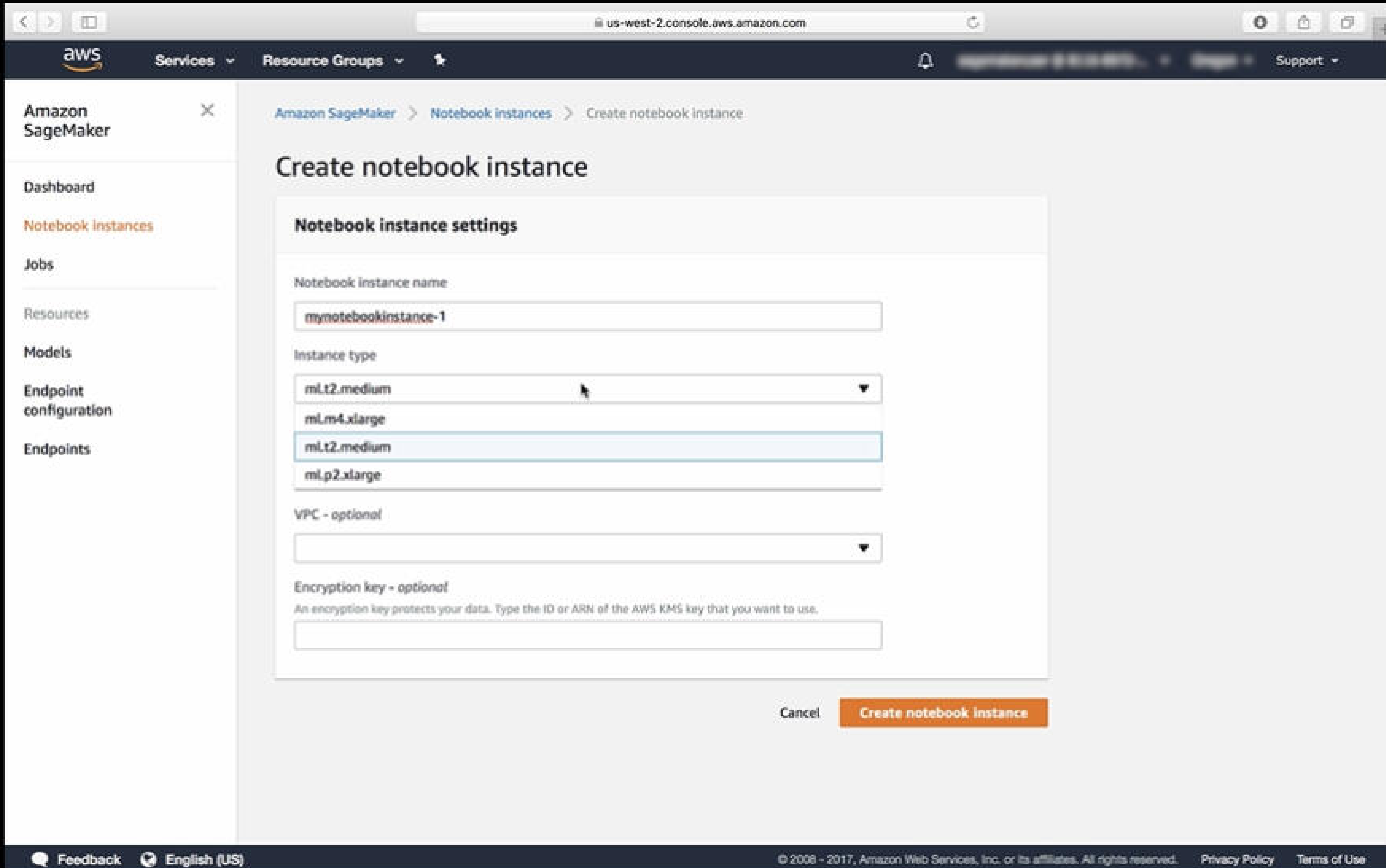
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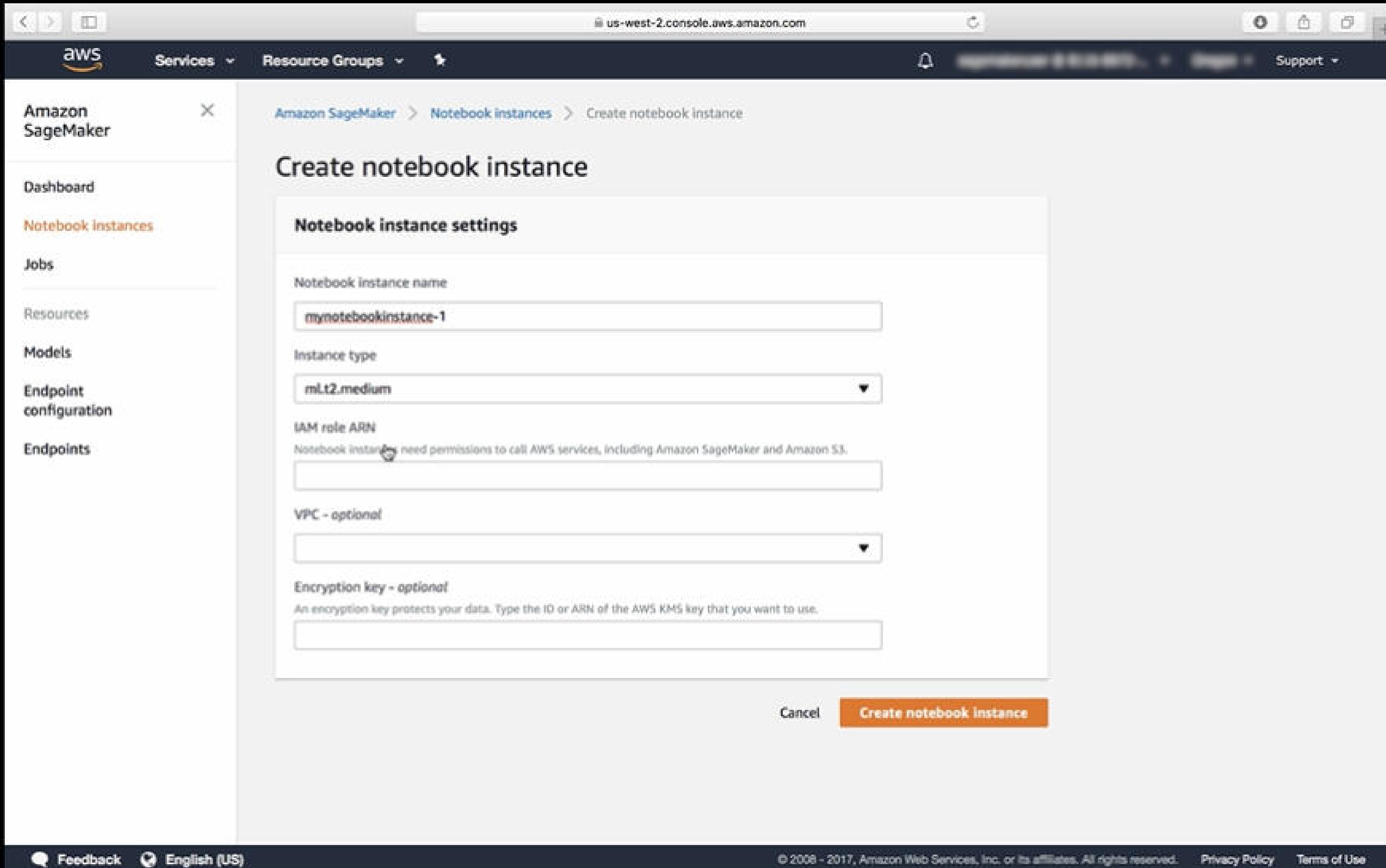
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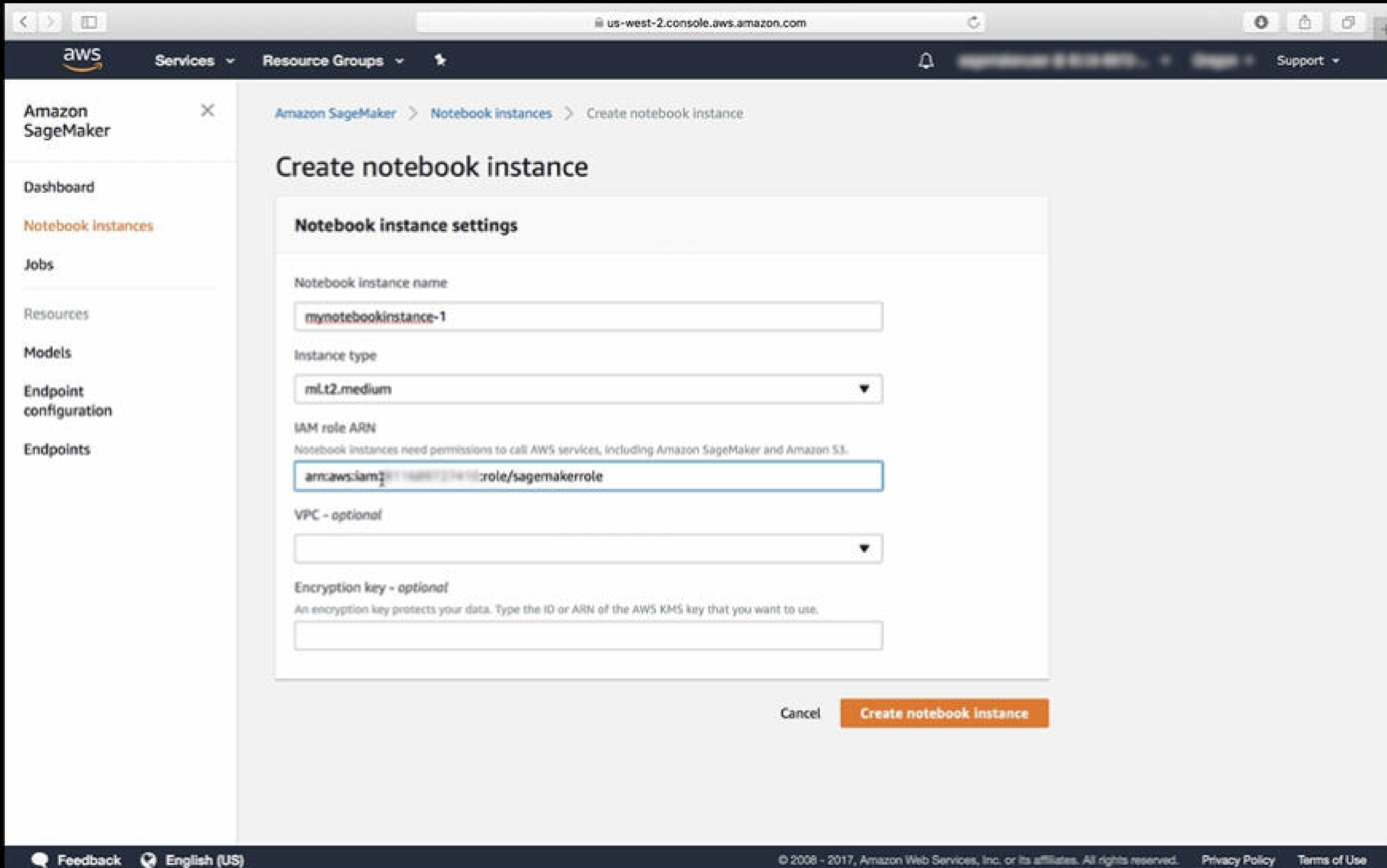
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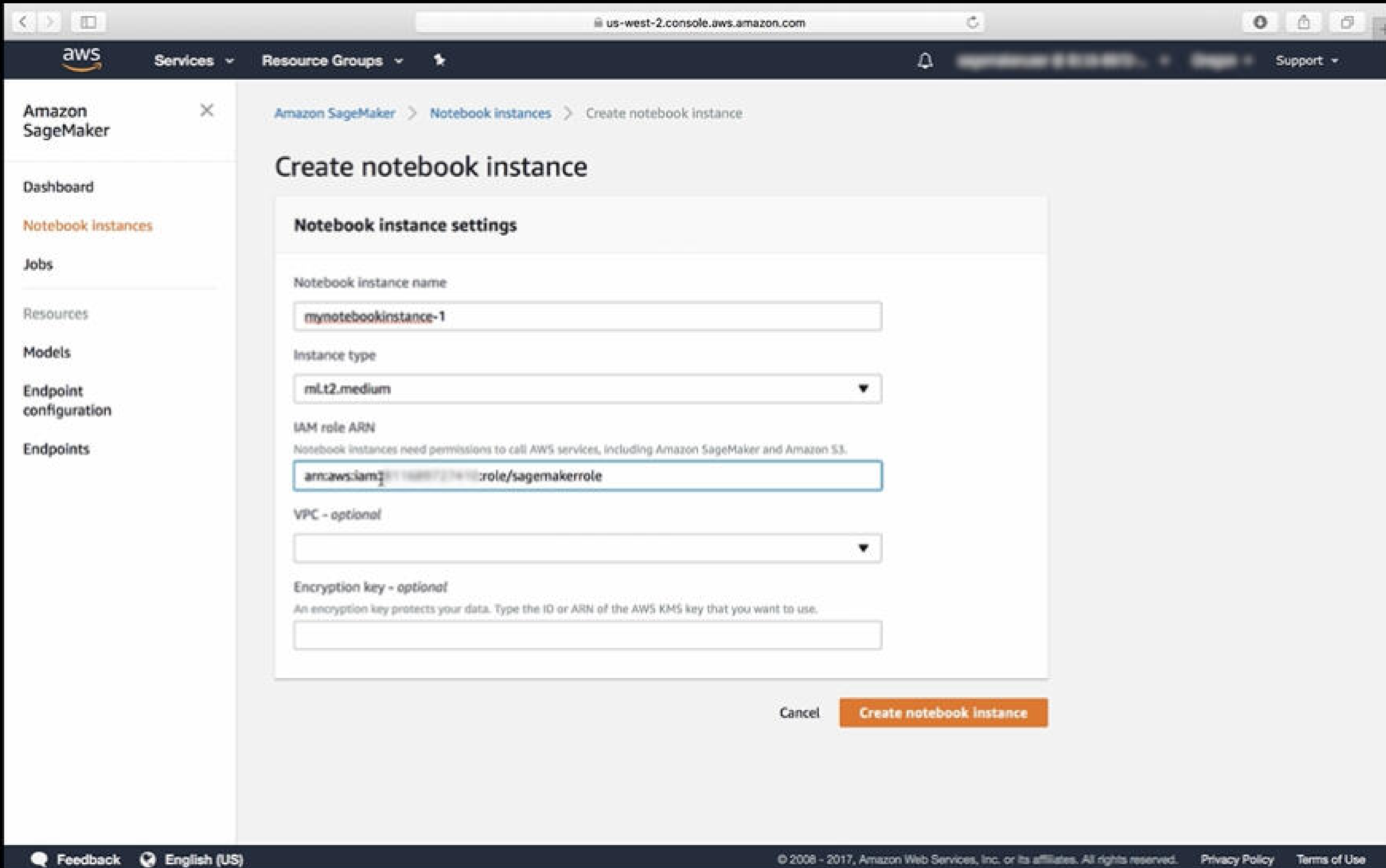
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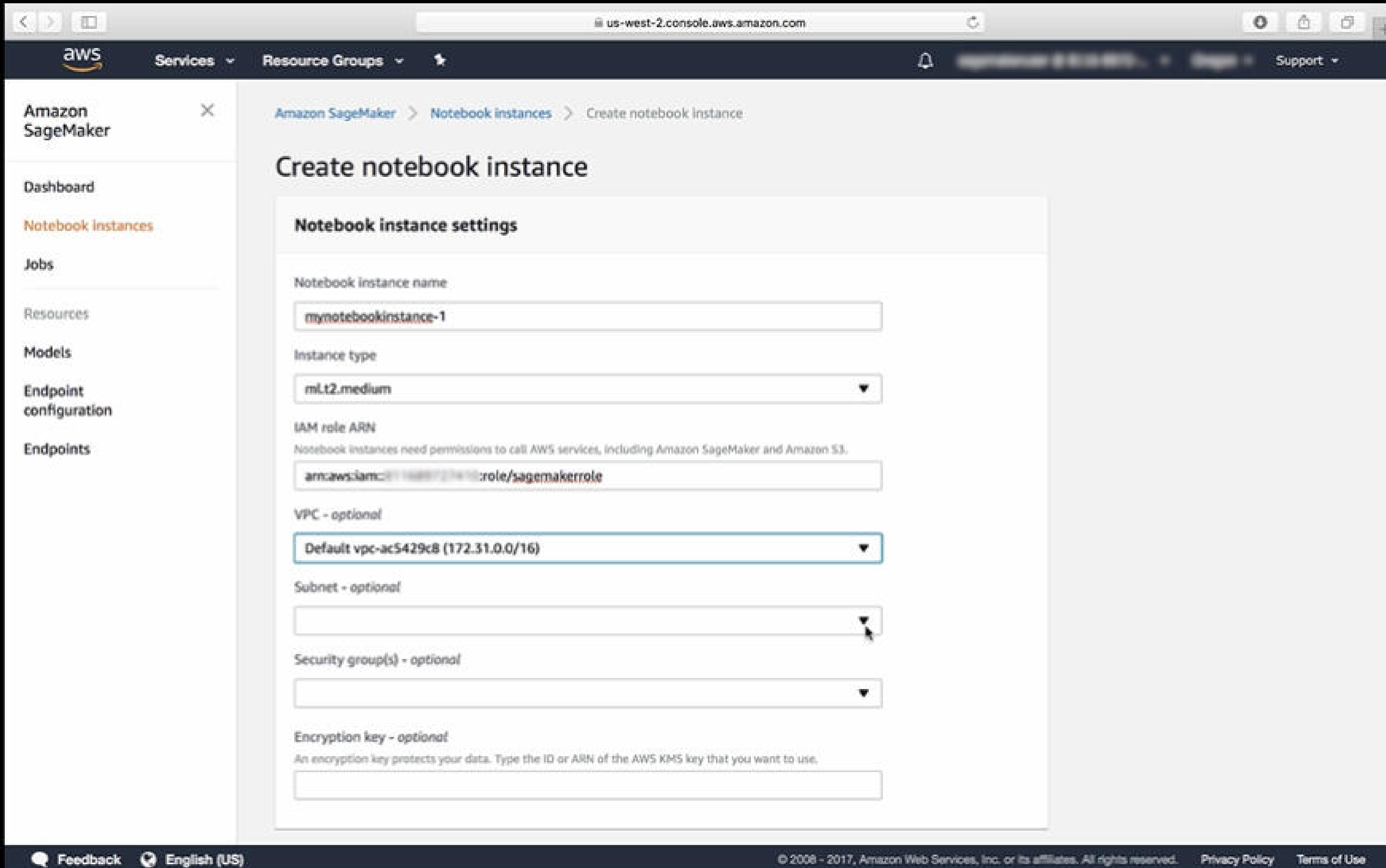

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VPC - optional
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Subnet - optional
Security group(s) - optional
Encryption key - optional
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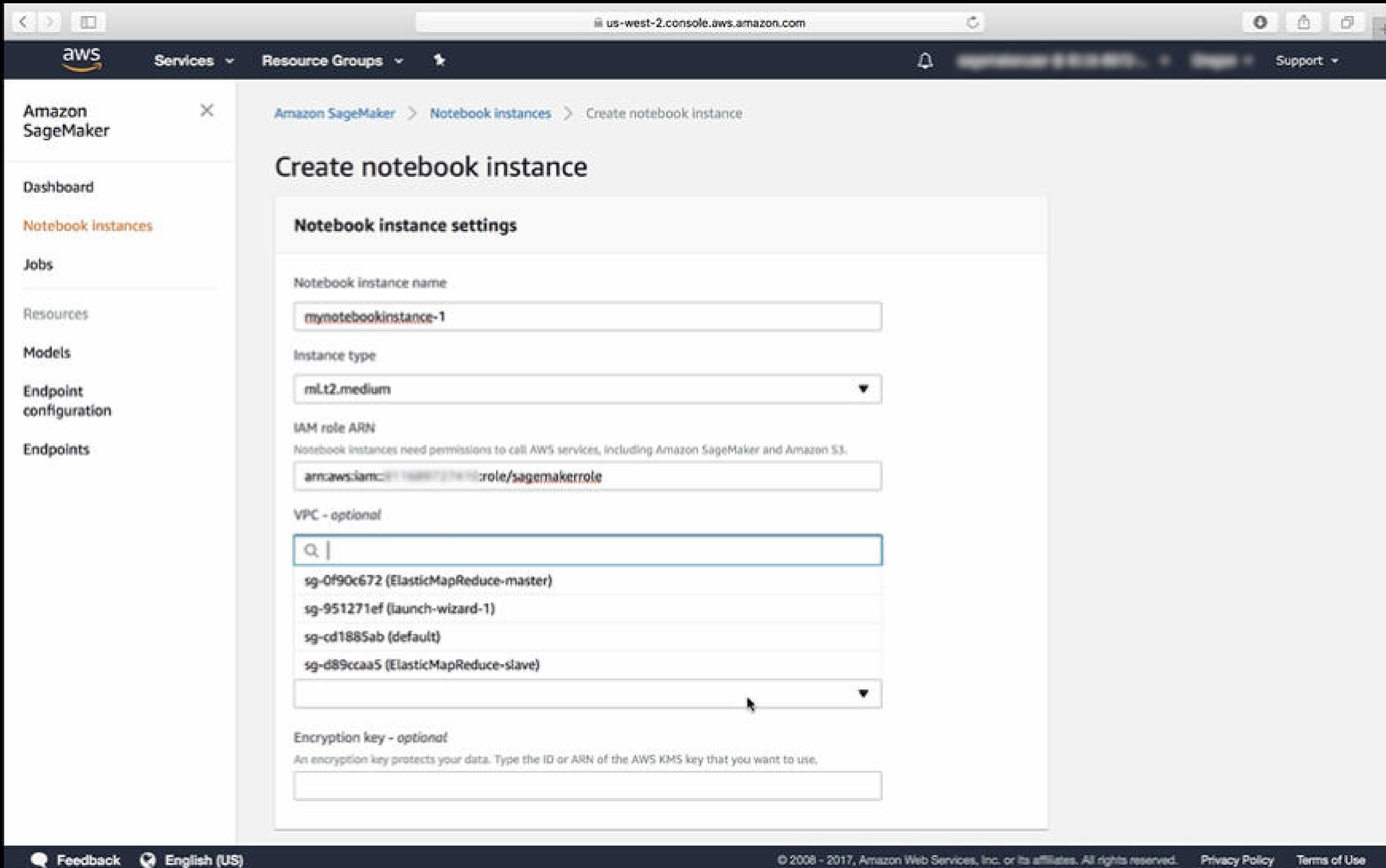
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VPC - optional
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sg-951271ef (launch-wizard-1)
sg-cd1885ab (default)
sg-d89ccaa5 (ElasticMapReduce-slave)
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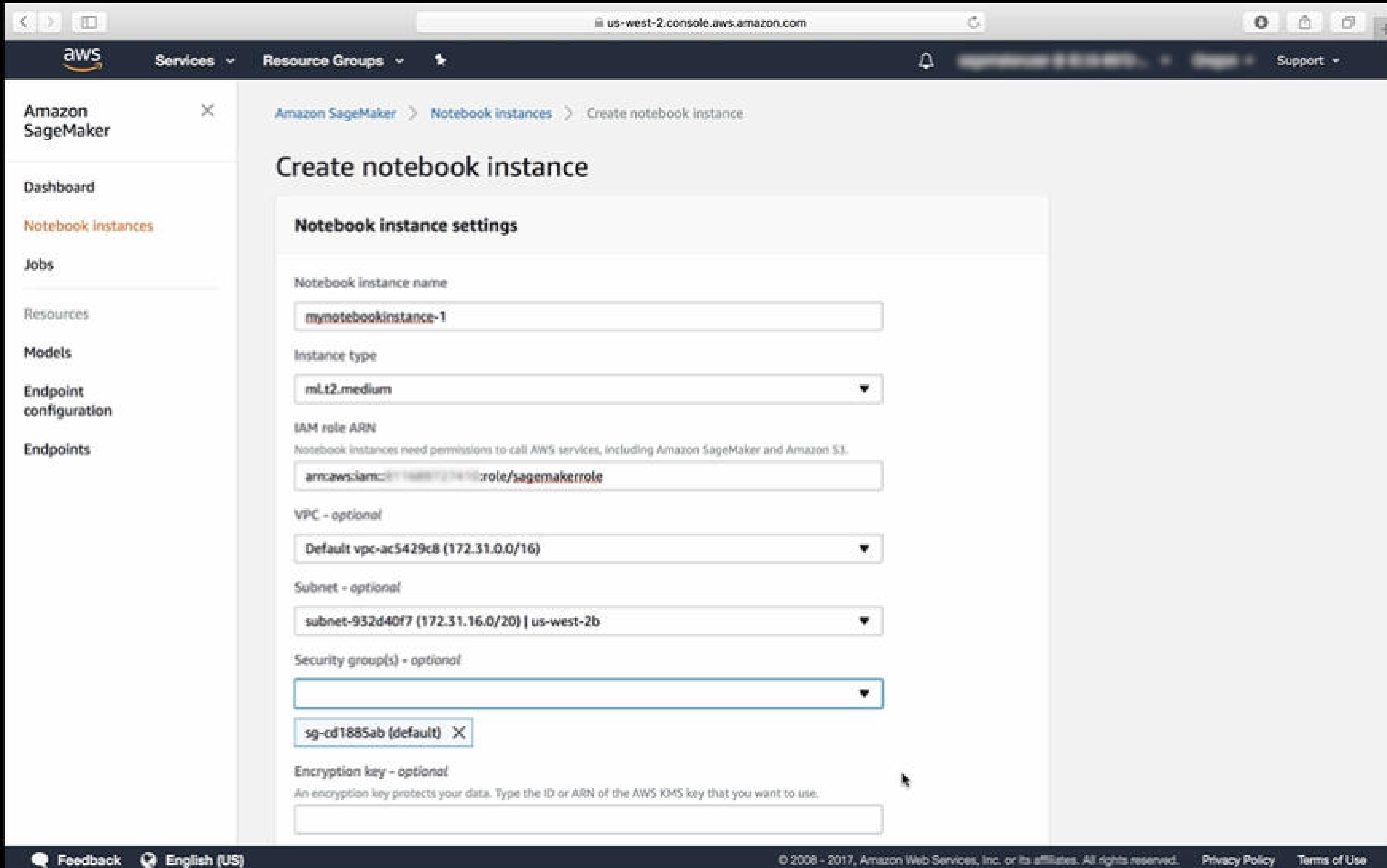
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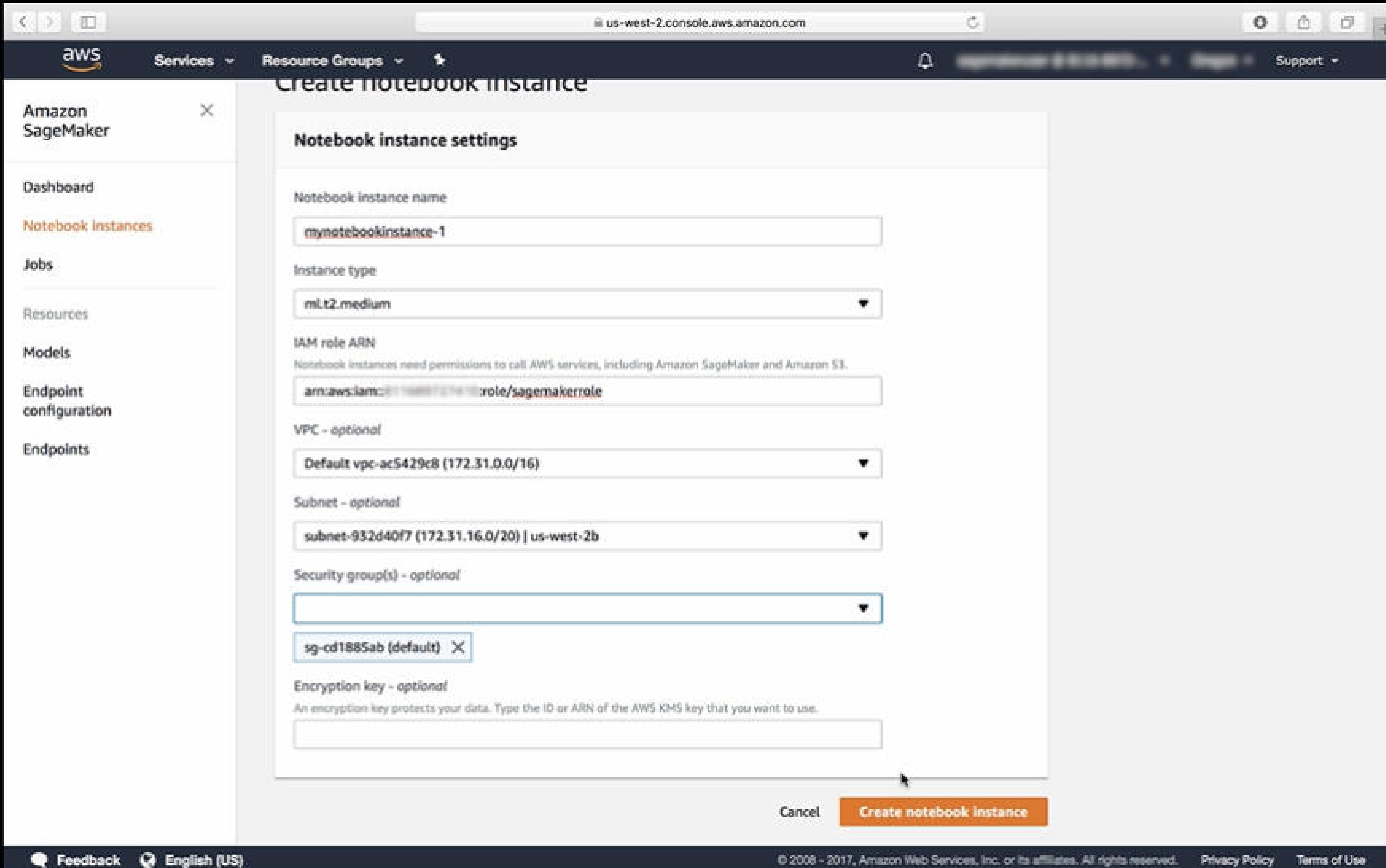

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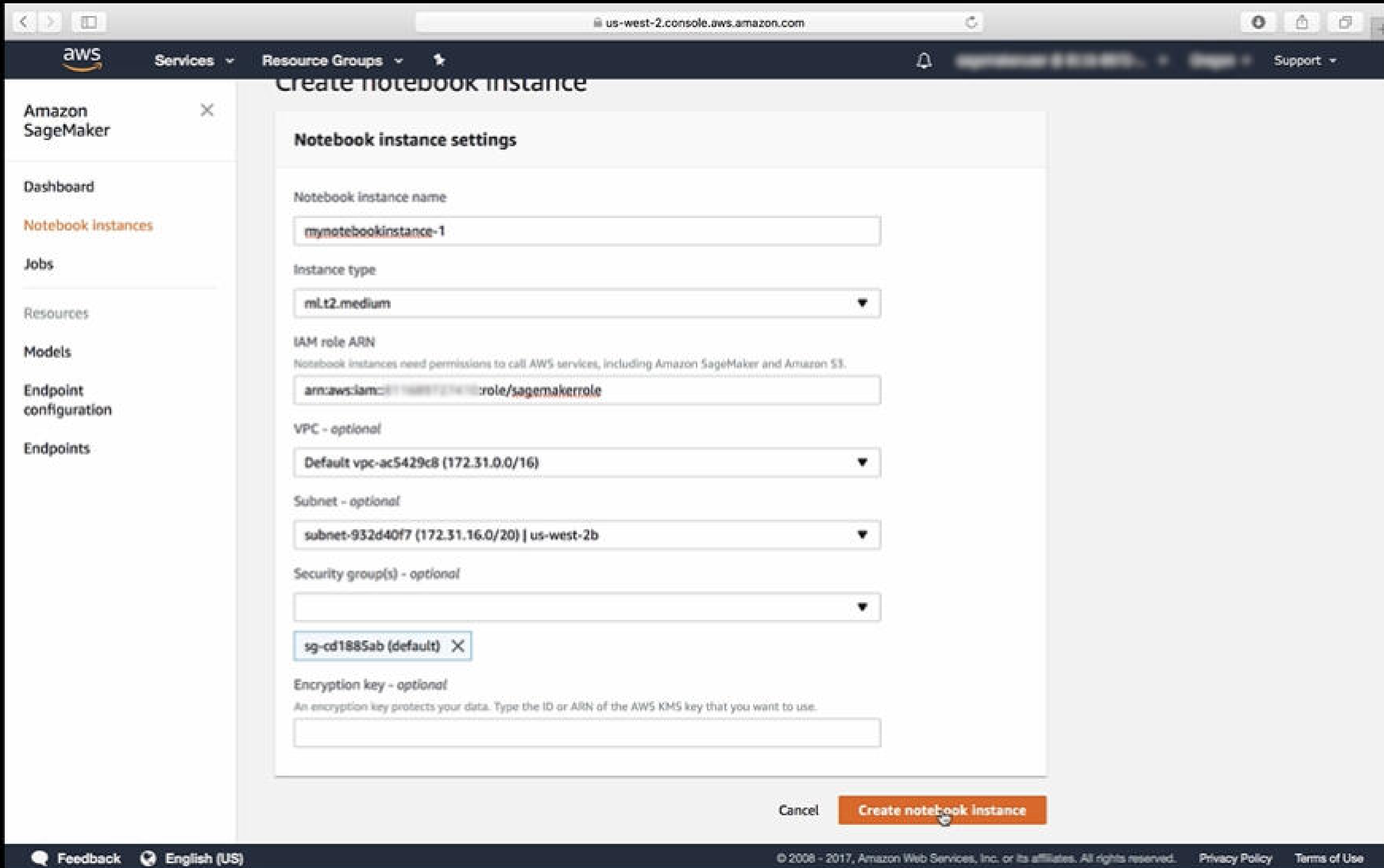
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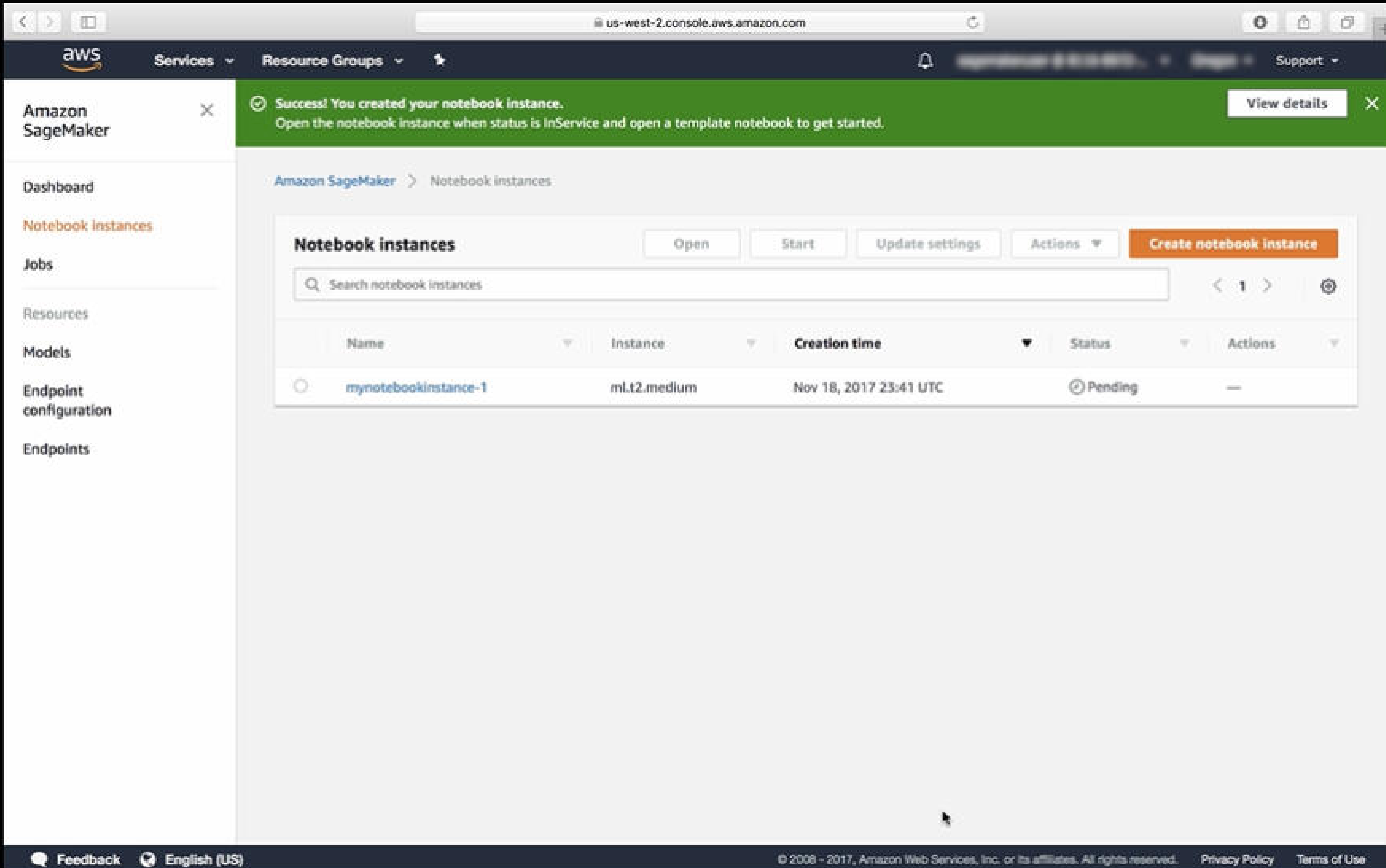

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Success! You created your notebook instance.
Open the notebook instance when status is InService and open a template notebook to get started.
View details
Amazon SageMaker > Notebook instances
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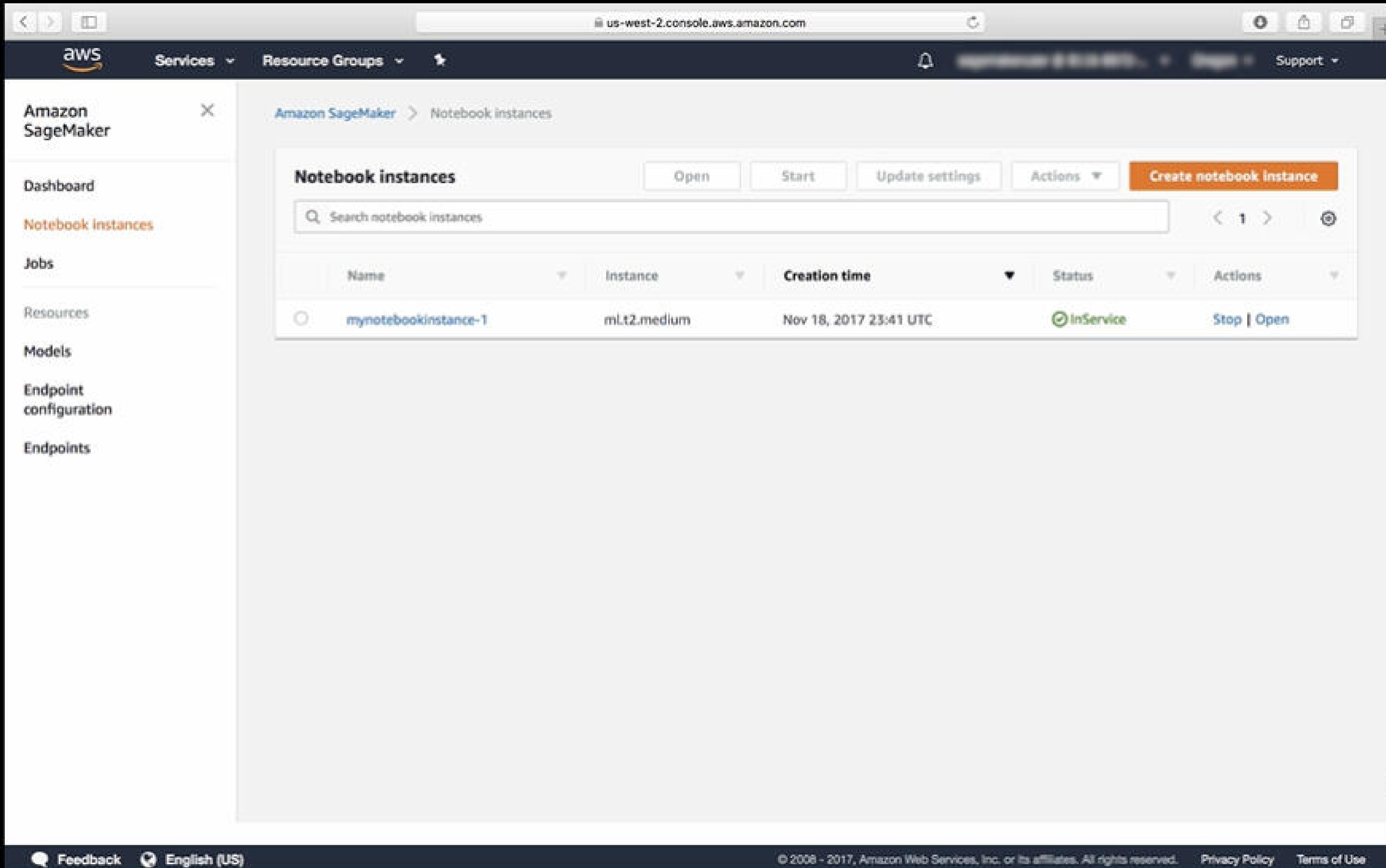
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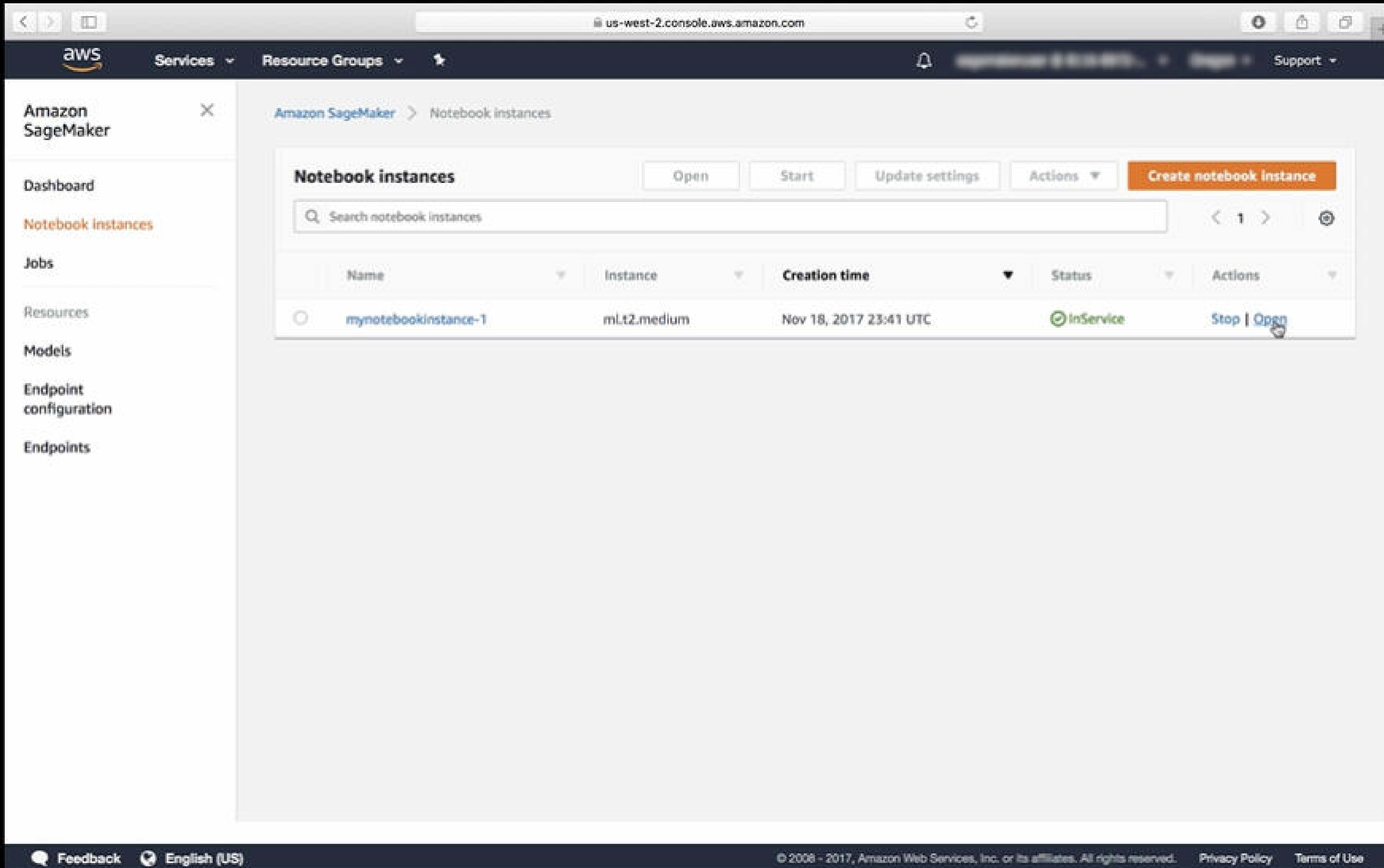
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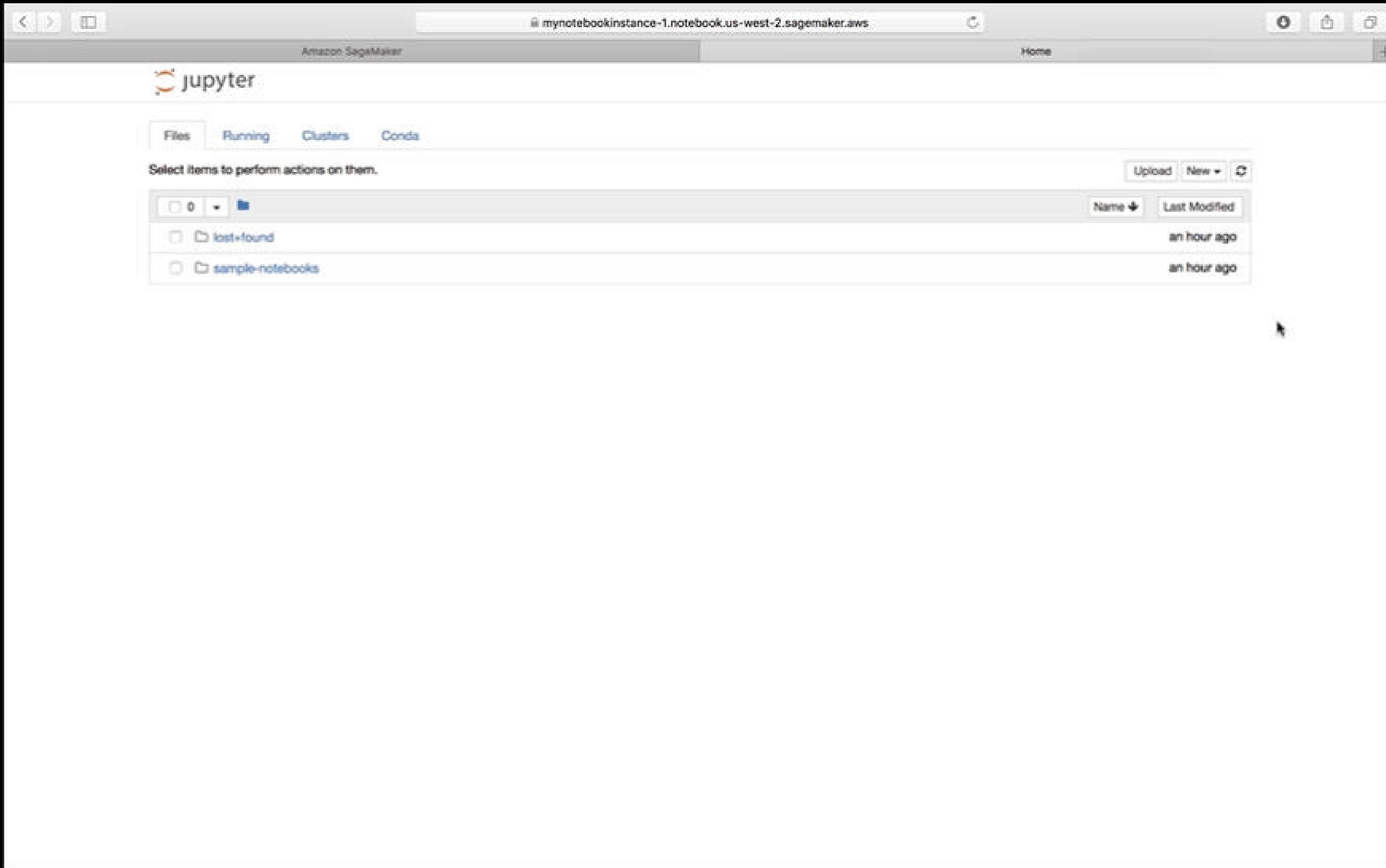
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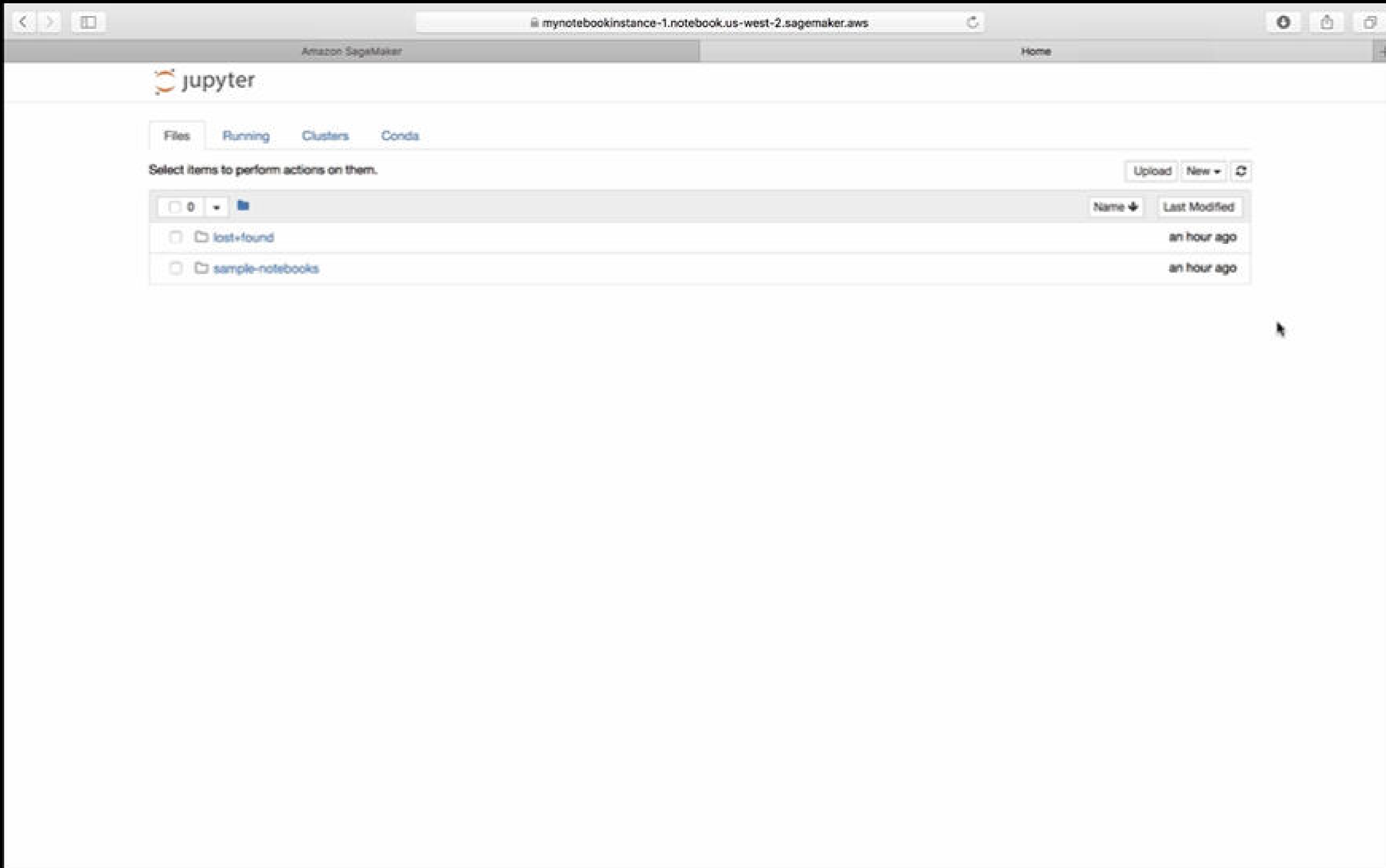
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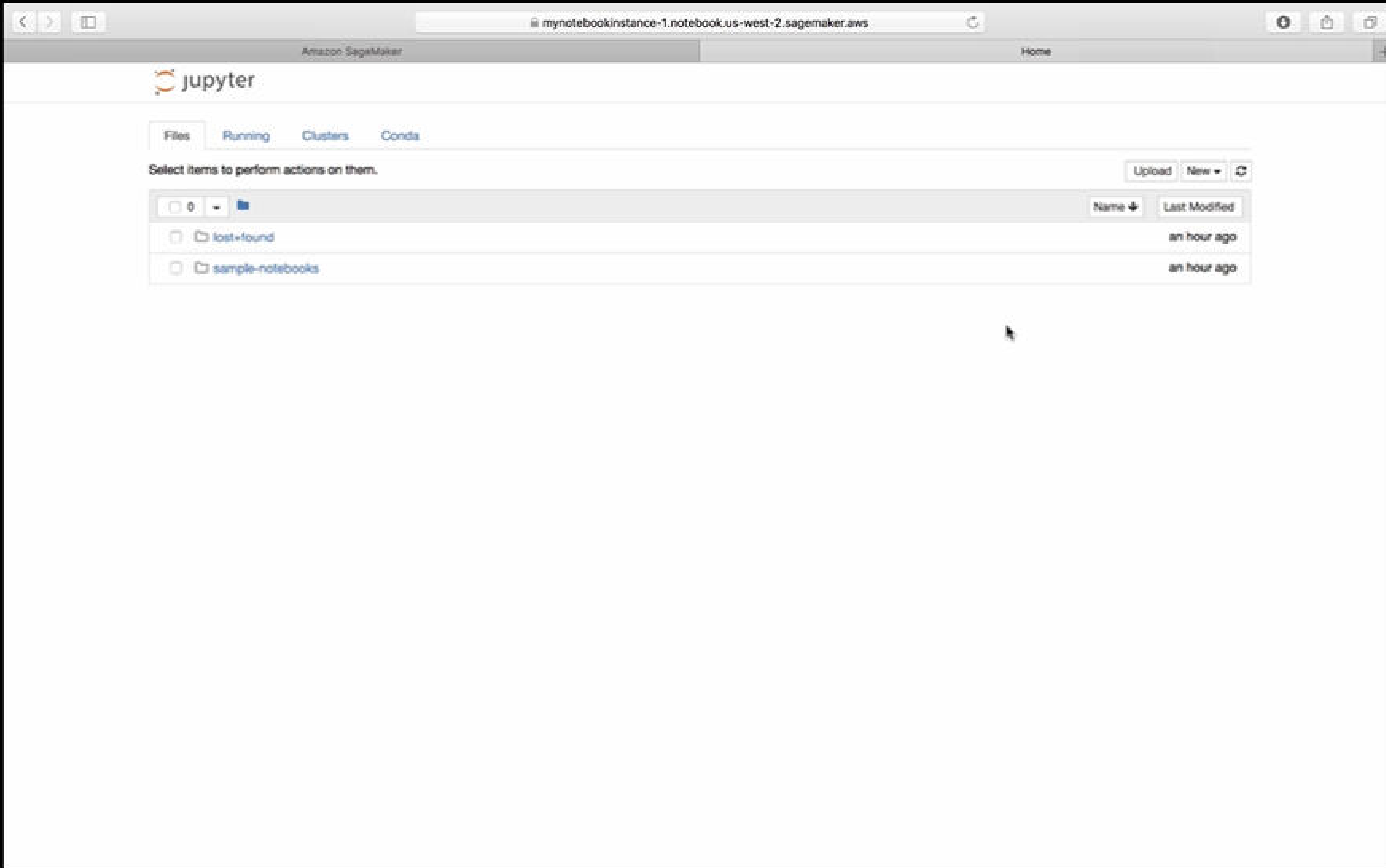
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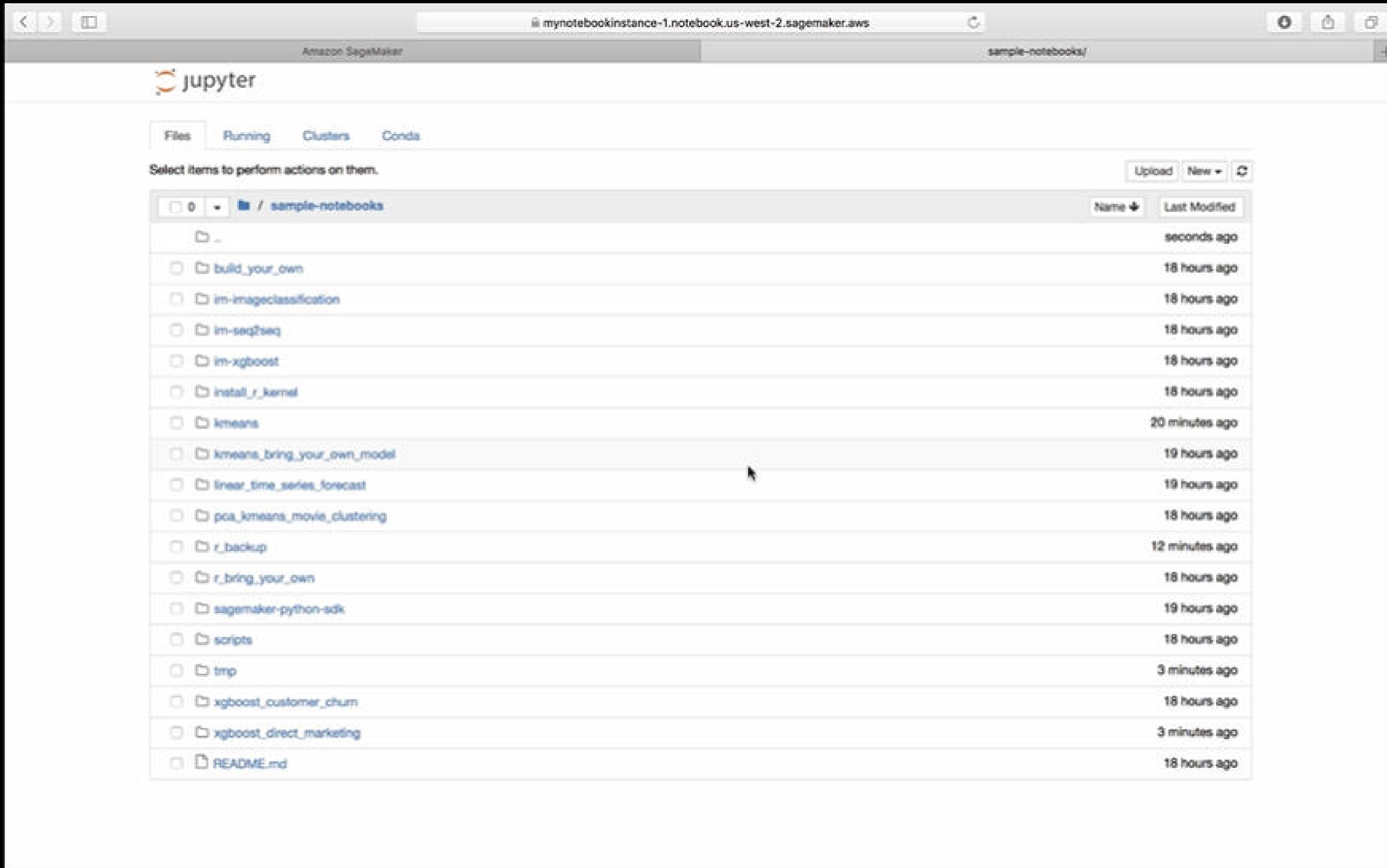
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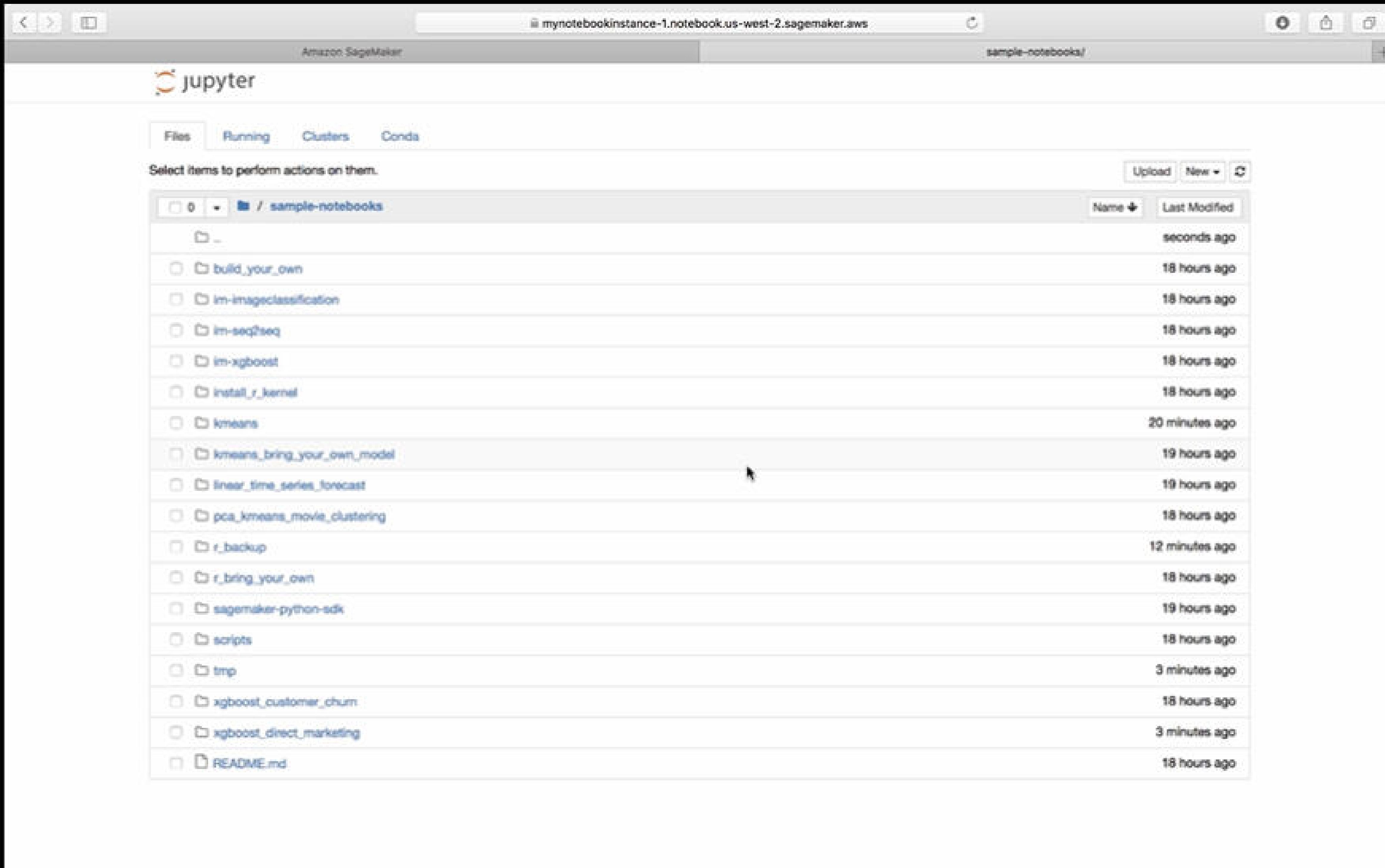
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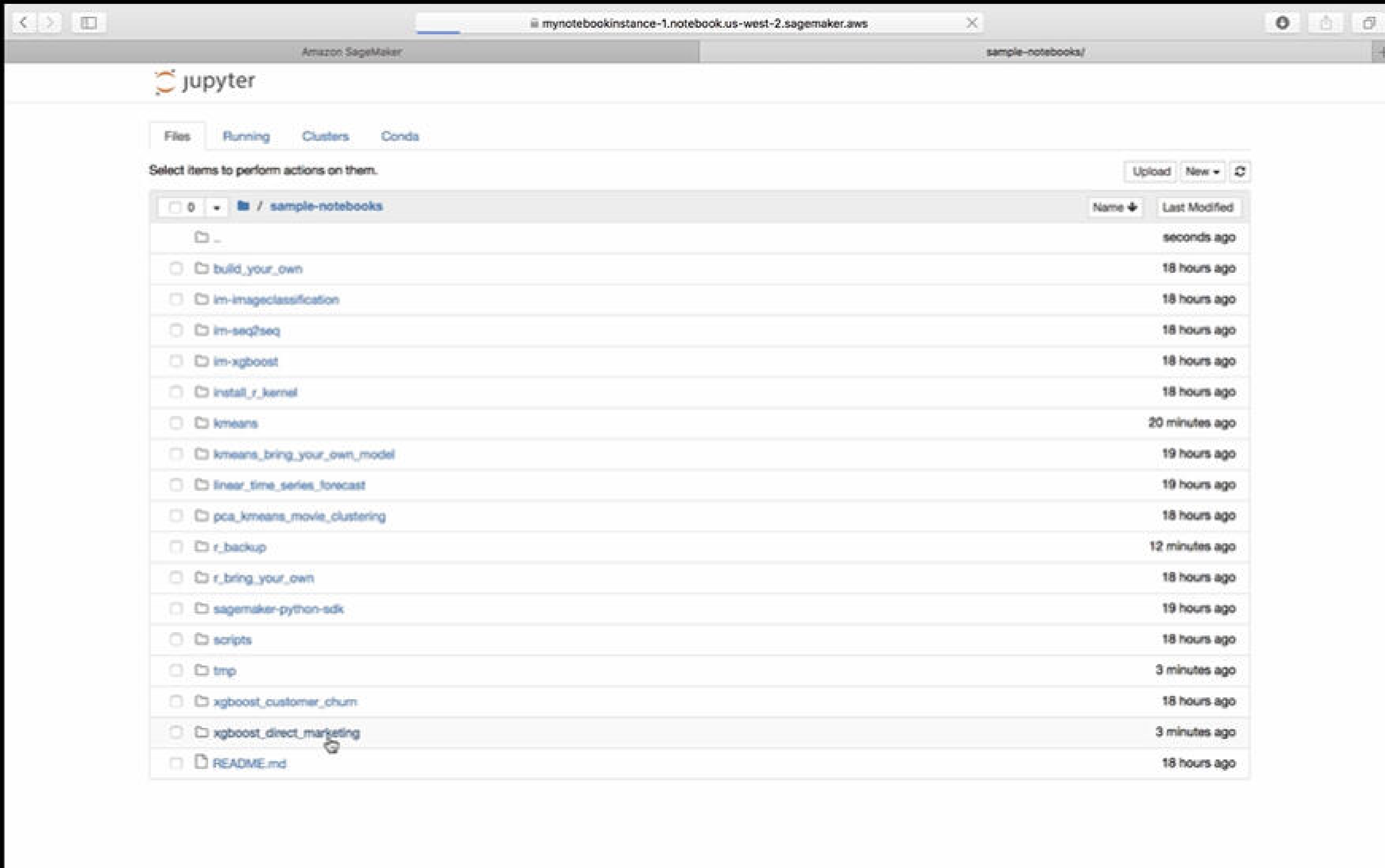
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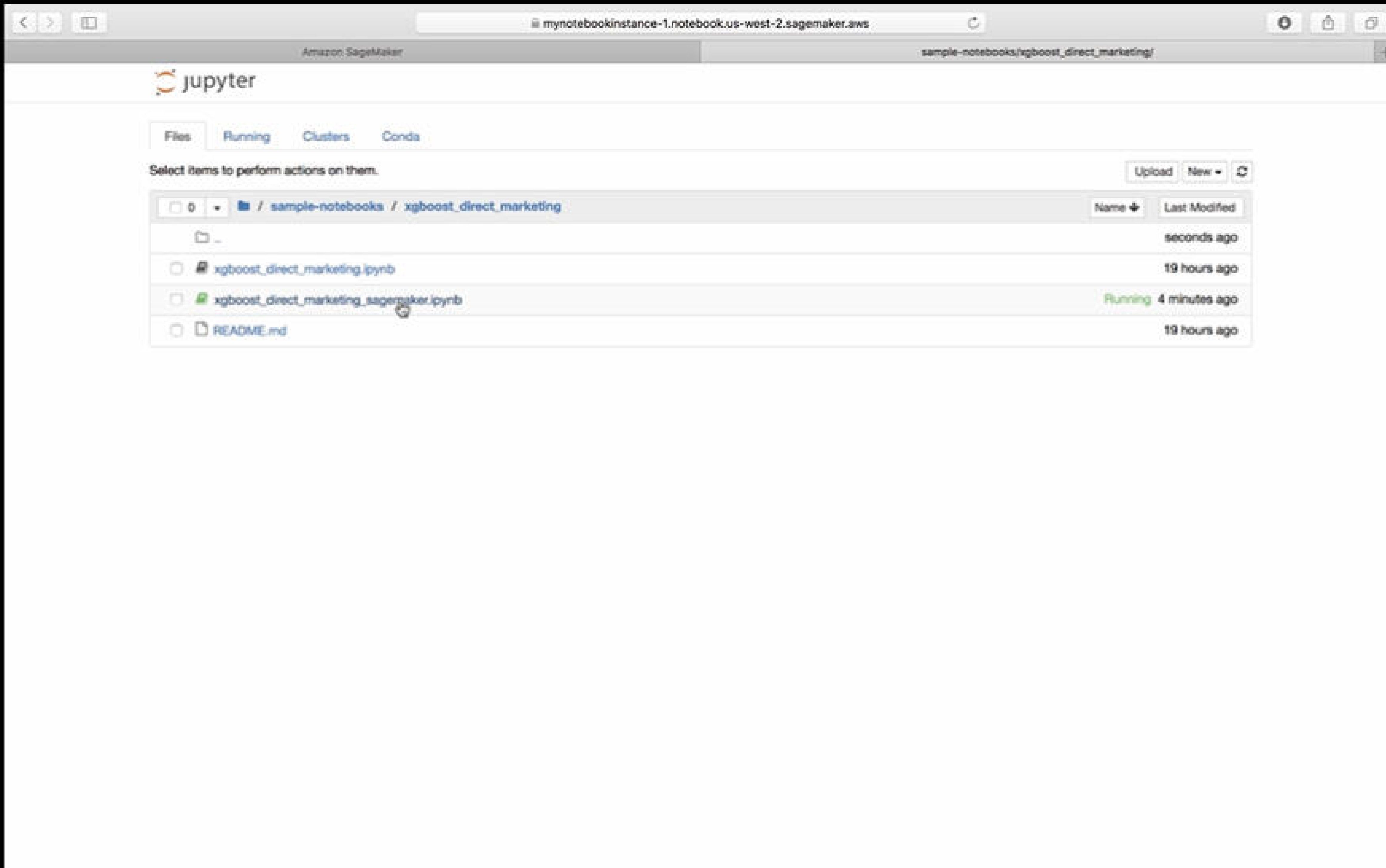
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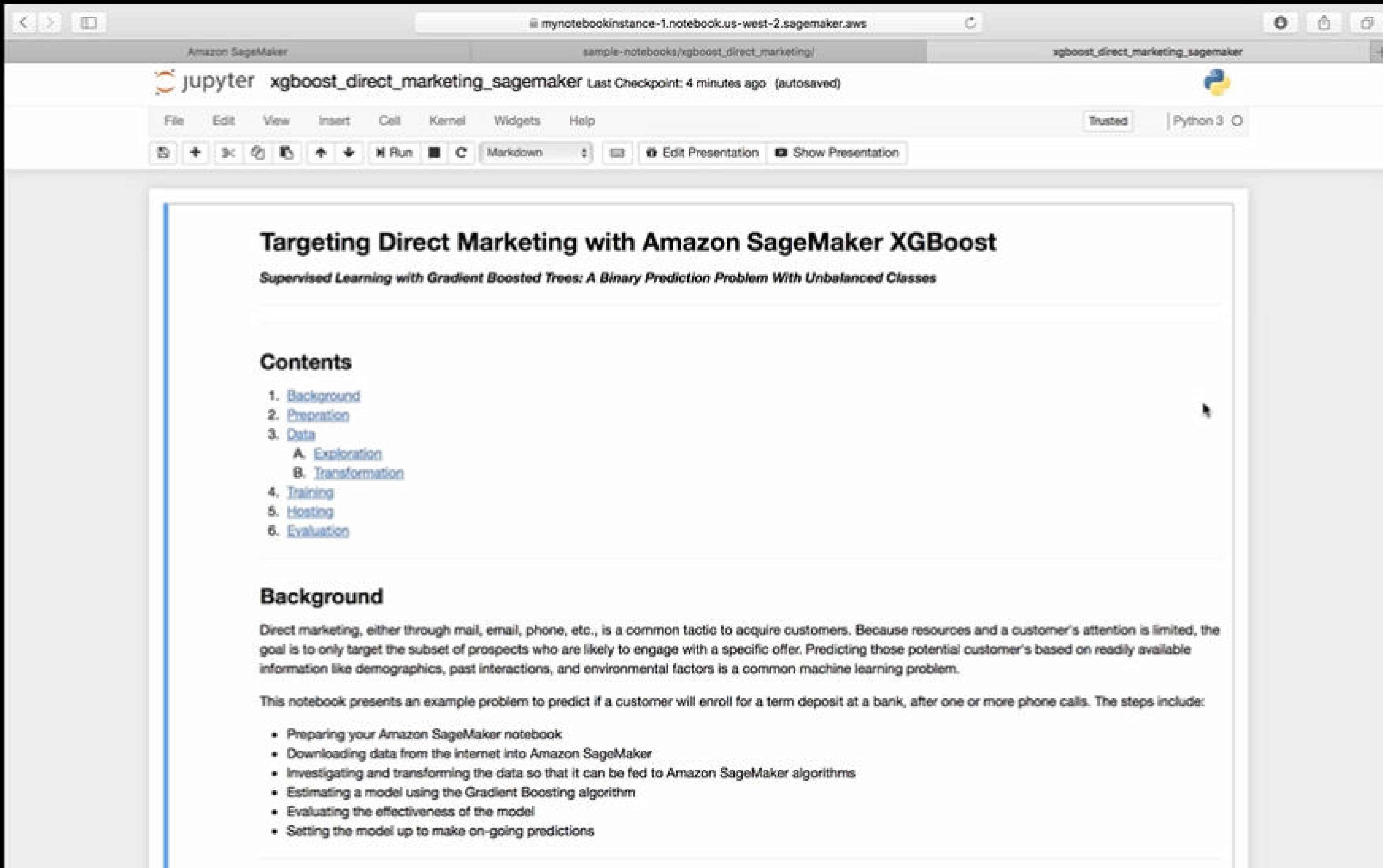
19 hours ago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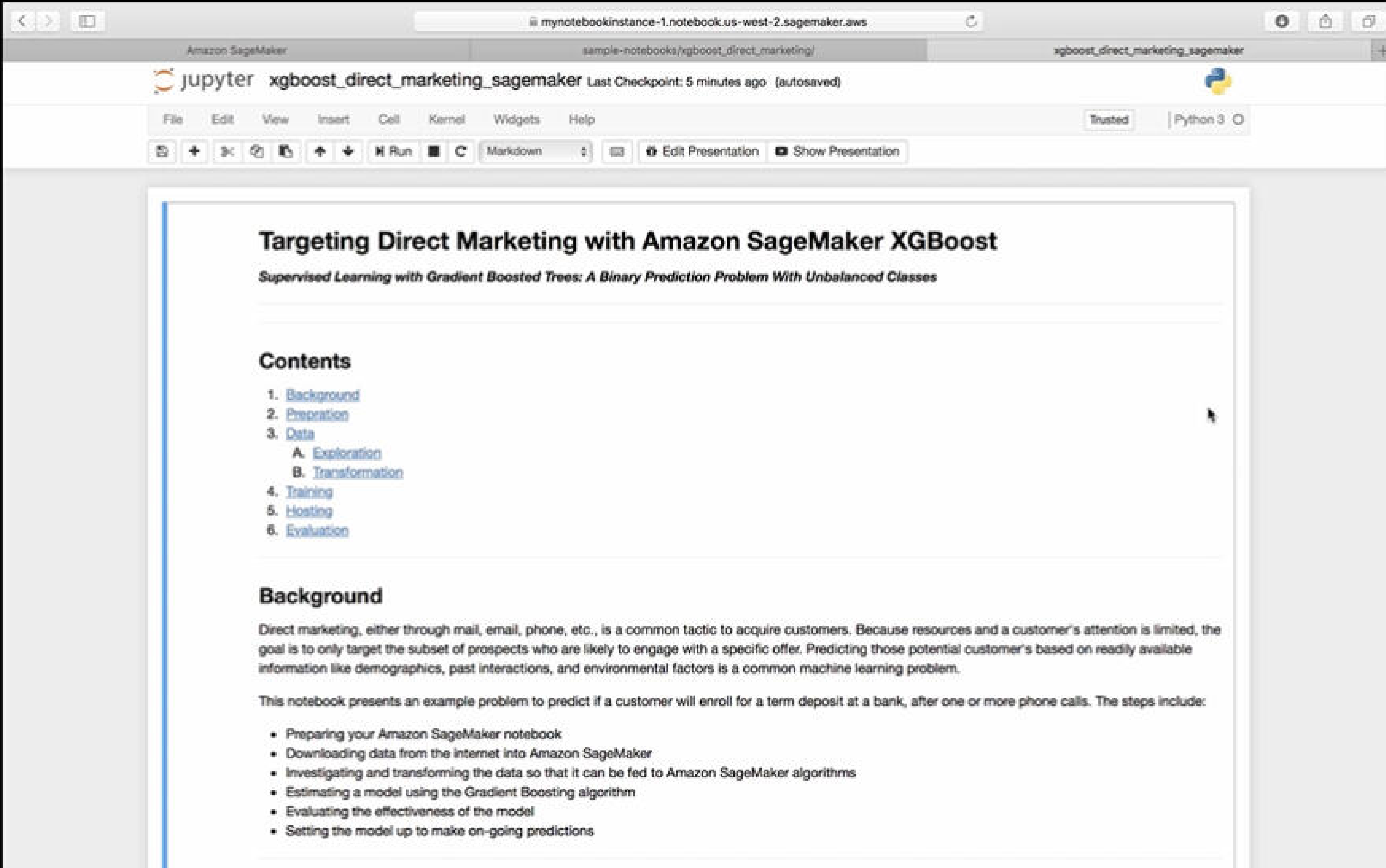
Targeting Direct Marketing with Amazon SageMaker XGBoost
Supervised Learning with Gradient Boosted Trees: A Binary Prediction Problem With Unbalanced Classes
Contents
1. Background
2. Prepration
3. Data
A. Exploration
B. Transformation
4. Training
5. Hosting
6. Evaluation
Background
Direct marketing, either through mail, email, phone, etc., is a common tactic to acquire customers. Because resources and a customer's attention is limited, the goal is to only target the subset of prospects who are likely to engage with a specific offer. Predicting those potential customer's based on readily available information like demographics, past interactions, and environmental factors is a common machine learning problem.
This notebook presents an example problem to predict if a customer will enroll for a term deposit at a bank, after one or more phone calls. The steps include:
• Preparing your Amazon SageMaker notebook
• Downloading data from the internet into Amazon SageMaker
• Investigating and transforming the data so that it can be fed to Amazon SageMaker algorithms
• Estimating a model using the Gradient Boosting algorithm
• Evaluating the effectiveness of the model
• Setting the model up to make on-going predictions



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Preparation

To start, let's define:

- IAM role for training/hosting to access resources
- The name of the S3 bucket we want to use
- An S3 prefix

In [1]:
```
import os
import boto3

role = 'arn:aws:iam::[redacted]:role/sagemakerrole'
bucket = 'sagemaker-pdx1'
prefix = 'xgboost'
```

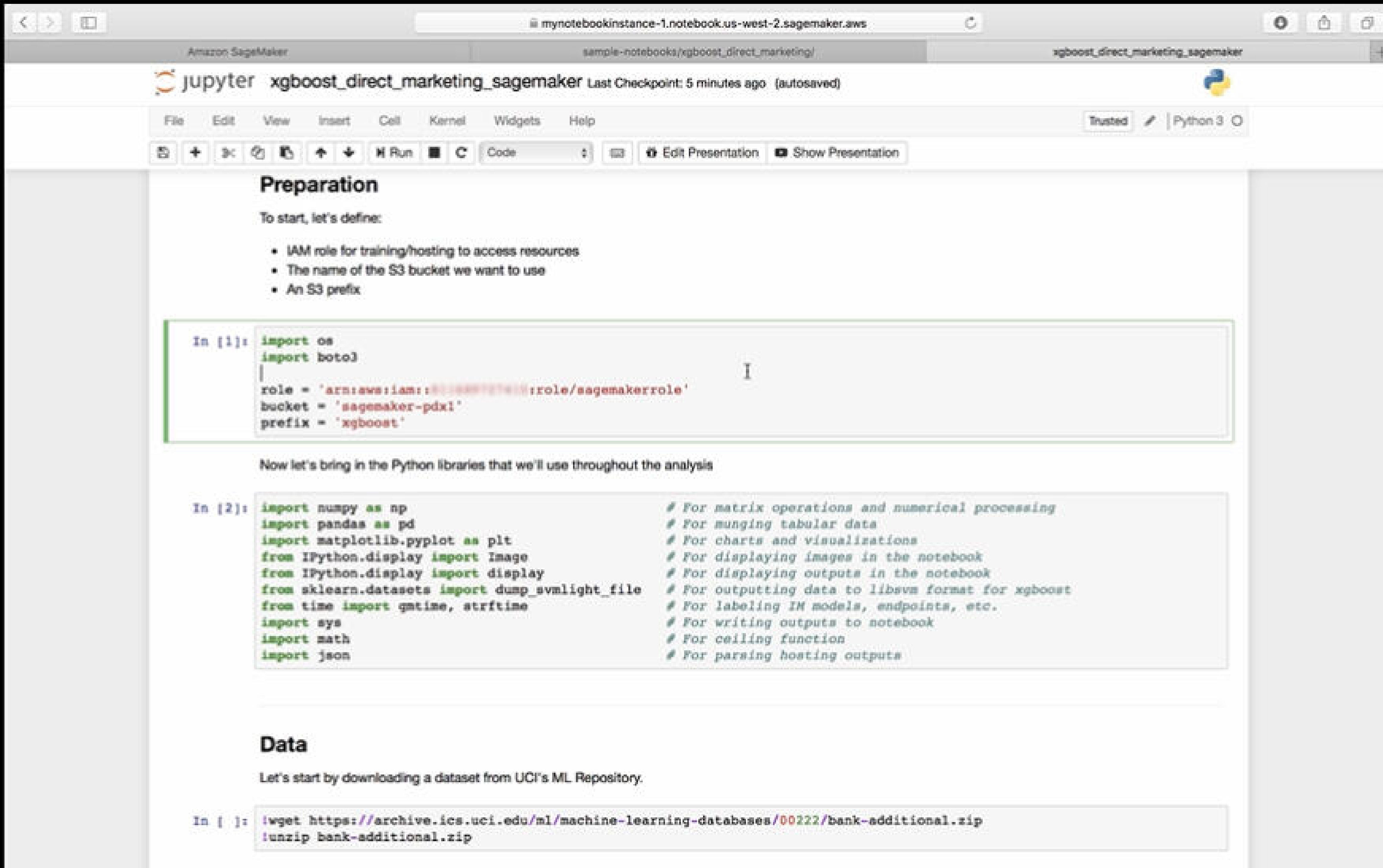
Now let's bring in the Python libraries that we'll use throughout the analysis

In [2]:
```
import numpy as np                                # For matrix operations and numerical processing
import pandas as pd                               # For munging tabular data
import matplotlib.pyplot as plt                   # For charts and visualizations
from IPython.display import Image                 # For displaying images in the notebook
from IPython.display import display               # For displaying outputs in the notebook
from sklearn.datasets import dump_svmlight_file   # For outputting data to libsvm format for xgboost
from time import gmtime, strftime                 # For labeling SM models, endpoints, etc.
import sys                                        # For writing outputs to notebook
import math                                       # For ceiling function
import json                                       # For parsing hosting outputs
```

Data

Let's start by downloading a dataset from UCI's ML Repository.

In [ ]:
```
!wget https://archive.ics.uci.edu/ml/machine-learning-databases/00222/bank-additional.zip
!unzip bank-additional.zip
```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Preparation

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In [12]:
```
import os
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role = 'arn:aws:iam::[illegible]:role/sagemakerrole'
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Now let's bring in the Python libraries that we'll use throughout the analysis

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```
import math                                        # For ceiling function
import json                                        # For parsing hosting outputs
```

Data

Let's start by downloading a dataset from UCI's ML Repository.

In [*]:

```
!wget https://archive.ics.uci.edu/ml/machine-learning-databases/00222/bank-additional.zip
!unzip bank-additional.zip
```

```
--2017-11-19 00:42:39--  https://archive.ics.uci.edu/ml/machine-learning-databases/00222/bank-additional.zip
Resolving archive.ics.uci.edu (archive.ics.uci.edu)... 128.195.10.249
Connecting to archive.ics.uci.edu (archive.ics.uci.edu)|128.195.10.249|:443... connected.
HTTP request sent, awaiting response... 200 OK
Length: 444572 (434K) [application/zip]
Saving to: 'bank-additional.zip'

bank-additional.zip   0%[                    ]       0  --.-KB/s
```

Now lets read this into a Pandas data frame and take a look.

In [ ]:

```
data = pd.read_csv('./bank-additional/bank-additional-full.csv', sep=';')
pd.set_option('display.max_columns', 500)     # Make sure we can see all of the columns
pd.set_option('display.max_rows', 20)         # Keep the output on one page
data
```

Let's talk about the data. At a high level, we can see:

- We have a little over 40K customer records, and 20 features for each customer
- The features are mixed; some numeric, some categorical
- The data appears to be sorted, at least by `time` and `contact`, maybe more

Specifics on each of the features:

Demographics:

- `age`: Customer's age (numeric)

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Out[15]:

	age	job	marital	education	default	housing	loan	contact	month	day_of_week	duration	campaign	pdays	previous	poutcome
0	56	housemaid	married	basic.4y	no	no	no	telephone	may	mon	261	1	999	0	nonexistent
1	57	services	married	high.school	unknown	no	no	telephone	may	mon	149	1	999	0	nonexistent
2	37	services	married	high.school	no	yes	no	telephone	may	mon	226	1	999	0	nonexistent
3	40	admin.	married	basic.6y	no	no	no	telephone	may	mon	151	1	999	0	nonexistent
4	56	services	married	high.school	no	no	yes	telephone	may	mon	307	1	999	0	nonexistent
5	45	services	married	basic.9y	unknown	no	no	telephone	may	mon	198	1	999	0	nonexistent
6	59	admin.	married	professional.course	no	no	no	telephone	may	mon	139	1	999	0	nonexistent
7	41	blue-collar	married	unknown	unknown	no	no	telephone	may	mon	217	1	999	0	nonexistent
8	24	technician	single	professional.course	no	yes	no	telephone	may	mon	380	1	999	0	nonexistent
9	25	services	single	high.school	no	yes	no	telephone	may	mon	50	1	999	0	nonexistent
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
41178	62	retired	married	university.degree	no	no	no	cellular	nov	thu	483	2	6	3	success
41179	64	retired	divorced	professional.course	no	yes	no	cellular	nov	fri	151	3	999	0	nonexistent
41180	36	admin.	married	university.degree	no	no	no	cellular	nov	fri	254	2	999	0	nonexistent
41181	37	admin.	married	university.degree	no	yes	no	cellular	nov	fri	281	1	999	0	nonexistent
41182	29	unemployed	single	basic.4y	no	yes	no	cellular	nov	fri	112	1	9	1	success
41183	73	retired	married	professional.course	no	yes	no	cellular	nov	fri	334	1	999	0	nonexistent
41184	46	blue-collar	married	professional.course	no	no	no	cellular	nov	fri	383	1	999	0	nonexistent
41185	56	retired	married	university.degree	no	yes	no	cellular	nov	fri	189	2	999	0	nonexistent
41186	44	technician	married	professional.course	no	no	no	cellular	nov	fri	442	1	999	0	nonexistent
41187	74	retired	married	professional.course	no	yes	no	cellular	nov	fri	239	3	999	1	failure

41188 rows × 21 columns

Let's talk about the data. At a high level, we can see:

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Out[15]:

loan	contact	month	day_of_week	duration	campaign	pdays	previous	poutcome	emp.var.rate	cons.price.idx	cons.conf.idx	euribor3m	nr.employed	y
no	telephone	may	mon	261	1	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191.0	no
no	telephone	may	mon	149	1	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191.0	no
no	telephone	may	mon	226	1	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191.0	no
no	telephone	may	mon	151	1	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191.0	no
yes	telephone	may	mon	307	1	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191.0	no
no	telephone	may	mon	198	1	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191.0	no
no	telephone	may	mon	139	1	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191.0	no
no	telephone	may	mon	217	1	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191.0	no
no	telephone	may	mon	380	1	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191.0	no
no	telephone	may	mon	50	1	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191.0	no
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
no	cellular	nov	thu	483	2	6	3	success	-1.1	94.767	-50.8	1.031	4963.6	yes
no	cellular	nov	fri	151	3	999	0	nonexistent	-1.1	94.767	-50.8	1.028	4963.6	no
no	cellular	nov	fri	254	2	999	0	nonexistent	-1.1	94.767	-50.8	1.028	4963.6	no
no	cellular	nov	fri	281	1	999	0	nonexistent	-1.1	94.767	-50.8	1.028	4963.6	yes
no	cellular	nov	fri	112	1	9	1	success	-1.1	94.767	-50.8	1.028	4963.6	no
no	cellular	nov	fri	334	1	999	0	nonexistent	-1.1	94.767	-50.8	1.028	4963.6	yes
no	cellular	nov	fri	383	1	999	0	nonexistent	-1.1	94.767	-50.8	1.028	4963.6	no
no	cellular	nov	fri	189	2	999	0	nonexistent	-1.1	94.767	-50.8	1.028	4963.6	no
no	cellular	nov	fri	442	1	999	0	nonexistent	-1.1	94.767	-50.8	1.028	4963.6	yes
no	cellular	nov	fri	239	3	999	1	failure	-1.1	94.767	-50.8	1.028	4963.6	no

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loan	contact	month	day_of_week	duration	campaign	pdays	previous	poutcome	emp.var.rate	cons.price.idx	cons.conf.idx	euribor3m	nr.employed	y
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no	telephone	may	mon	226	1	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191.0	no
no	telephone	may	mon	151	1	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191.0	no
yes	telephone	may	mon	307	1	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191.0	no
no	telephone	may	mon	198	1	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191.0	no
no	telephone	may	mon	139	1	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191.0	no
no	telephone	may	mon	217	1	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191.0	no
no	telephone	may	mon	380	1	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191.0	no
no	telephone	may	mon	50	1	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191.0	no
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
no	cellular	nov	thu	483	2	6	3	success	-1.1	94.767	-50.8	1.031	4963.6	yes
no	cellular	nov	fri	151	3	999	0	nonexistent	-1.1	94.767	-50.8	1.028	4963.6	no
no	cellular	nov	fri	254	2	999	0	nonexistent	-1.1	94.767	-50.8	1.028	4963.6	no
no	cellular	nov	fri	281	1	999	0	nonexistent	-1.1	94.767	-50.8	1.028	4963.6	yes
no	cellular	nov	fri	112	1	9	1	success	-1.1	94.767	-50.8	1.028	4963.6	no
no	cellular	nov	fri	334	1	999	0	nonexistent	-1.1	94.767	-50.8	1.028	4963.6	yes
no	cellular	nov	fri	383	1	999	0	nonexistent	-1.1	94.767	-50.8	1.028	4963.6	no
no	cellular	nov	fri	189	2	999	0	nonexistent	-1.1	94.767	-50.8	1.028	4963.6	no
no	cellular	nov	fri	442	1	999	0	nonexistent	-1.1	94.767	-50.8	1.028	4963.6	yes
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no	telephone	may	mon	198	1	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191.0	no
no	telephone	may	mon	139	1	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191.0	no
no	telephone	may	mon	217	1	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191.0	no
no	telephone	may	mon	380	1	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191.0	no
no	telephone	may	mon	50	1	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191.0	no
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
no	cellular	nov	thu	483	2	6	3	success	-1.1	94.767	-50.8	1.031	4963.6	yes
no	cellular	nov	fri	151	3	999	0	nonexistent	-1.1	94.767	-50.8	1.028	4963.6	no
no	cellular	nov	fri	254	2	999	0	nonexistent	-1.1	94.767	-50.8	1.028	4963.6	no
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no	cellular	nov	fri	189	2	999	0	nonexistent	-1.1	94.767	-50.8	1.028	4963.6	no
no	cellular	nov	fri	442	1	999	0	nonexistent	-1.1	94.767	-50.8	1.028	4963.6	yes
no	cellular	nov	fri	239	3	999	1	failure	-1.1	94.767	-50.8	1.028	4963.6	no

Let's talk about the data. At a high level, we can see:

- We have a little over 40K customer records, and 20 features for each customer

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Let's talk about the data. At a high level, we can see:

- We have a little over 40K customer records, and 20 features for each customer
- The features are mixed; some numeric, some categorical
- The data appears to be sorted, at least by `time` and `contact`, maybe more

Specifics on each of the features:

Demographics:

- `age`: Customer's age (numeric)
- `job`: Type of job (categorical: 'admin.', 'services', ...)
- `marital`: Marital status (categorical: 'married', 'single', ...)
- `education`: Level of education (categorical: 'basic.4y', 'high.school', ...)

Past customer events:

- `default`: Has credit in default? (categorical: 'no', 'unknown', ...)
- `housing`: Has housing loan? (categorical: 'no', 'yes', ...)
- `loan`: Has personal loan? (categorical: 'no', 'yes', ...)

Past direct marketing contacts:

- `contact`: Contact communication type (categorical: 'cellular', 'telephone', ...)
- `month`: Last contact month of year (categorical: 'may', 'nov', ...)
- `day_of_week`: Last contact day of the week (categorical: 'mon', 'fri', ...)
- `duration`: Last contact duration, in seconds (numeric). Important note: If duration = 0 then `y` = 'no'.

Campaign information:

- `campaign`: Number of contacts performed during this campaign and for this client (numeric, includes last contact)
- `pdays`: Number of days that passed by after the client was last contacted from a previous campaign (numeric)
- `previous`: Number of contacts performed before this campaign and for this client (numeric)
- `poutcome`: Outcome of the previous marketing campaign (categorical: 'nonexistent','success', ...)

External environment factors:

Target variable:

- `y`: Has the client subscribed a term deposit? (binary: 'yes','no')

Exploration

Let's start exploring the data. First, let's understand how the features are distributed.

In [ ]:
```
# Frequency tables for each categorical feature
for column in data.select_dtypes(include=['object']).columns:
    display(pd.crosstab(index=data[column], columns='% observations', normalize='columns'))

# Histograms for each numeric features
display(data.describe())
%matplotlib inline
hist = data.hist(bins=30, sharey=True, figsize=(10, 10))
```

Notice that:

- Almost 90% of the values for our target variable `y` are "no", so most customers did not subscribe to a term deposit.
- Many of the predictive features take on values of "unknown". Some are more common than others. We should think carefully as to what causes a value of "unknown" (are these customers non-representative in some way?) and how we that should be handled.
  - Even if "unknown" is included as it's own distinct category, what does it mean given that, in reality, those observations likely fall within one of the other categories of that feature?
- Many of the predictive features have categories with very few observations in them. If we find a small category to be highly predictive of our target outcome, do we have enough evidence to make a generalization about that?
- Contact timing is particularly skewed. Almost a third in May and less than 1% in December. What does this mean for predicting our target variable next December?
- There are no missing values in our numeric features. Or missing values have already been imputed.
  - `pdays` takes a value near 1000 for almost all customers. Likely a placeholder value signifying no previous contact.
- Several numeric features have a very long tail. Do we need to handle these few observations with extremely large values differently?
- Several numeric features (particularly the macroeconomic ones) occur in distinct buckets. Should these be treated as categorical?

Next, let's look at how our features relate to the target that we are attempting to predict.

In [ ]:
```
display(data.corr())
```

admin.	0.253035
blue-collar	0.224677
entrepreneur	0.035350
housemaid	0.025736
management	0.070992
retired	0.041760
self-employed	0.034500
services	0.096363
student	0.021244
technician	0.163713

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Notice that:

- Features vary widely in their relationship with one another. Some with highly negative correlation, others with highly positive correlation.

- Many of the predictive features take on values of "unknown". Some are more common than others. We should think carefully as to what causes a value of "unknown" (are these customers non-representative in some way?) and how we that should be handled.
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In [17]:
```
display(data.corr())
```

	age	duration	campaign	pdays	previous	emp.var.rate	cons.price.idx	cons.conf.idx	euribor3m	nr.employed
age	1.000000	-0.000866	0.004594	-0.034369	0.024365	-0.000371	0.000857	0.129372	0.010767	-0.017725
duration	-0.000866	1.000000	-0.071699	-0.047577	0.020640	-0.027968	0.005312	-0.008173	-0.032897	-0.044703
campaign	0.004594	-0.071699	1.000000	0.052584	-0.079141	0.150754	0.127836	-0.013733	0.135133	0.144095
pdays	-0.034369	-0.047577	0.052584	1.000000	-0.587514	0.271004	0.078889	-0.091342	0.296899	0.372605
previous	0.024365	0.020640	-0.079141	-0.587514	1.000000	-0.420489	-0.203130	-0.050936	-0.454494	-0.501333
emp.var.rate	-0.000371	-0.027968	0.150754	0.271004	-0.420489	1.000000	0.775334	0.196041	0.972245	0.906970
cons.price.idx	0.000857	0.005312	0.127836	0.078889	-0.203130	0.775334	1.000000	0.058986	0.688230	0.522034
cons.conf.idx	0.129372	-0.008173	-0.013733	-0.091342	-0.050936	0.196041	0.058986	1.000000	0.277686	0.100513
euribor3m	0.010767	-0.032897	0.135133	0.296899	-0.454494	0.972245	0.688230	0.277686	1.000000	0.945154
nr.employed	-0.017725	-0.044703	0.144095	0.372605	-0.501333	0.906970	0.522034	0.100513	0.945154	1.000000

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- Handling missing values: Some machine learning algorithms are capable of handling missing values, but most would rather not. Options include:
  - Removing observations with missing values: This works well if only a very small fraction of observations have incomplete information.
  - Remove features with missing values: This works well if there are a small number of features which have a large number of missing values.
  - Imputing missing values: Entire books have been written on this topic, but common choices are replacing the missing value with the mode or mean of that column's non-missing values.
- Converting categorical to numeric: The most common method is one hot encoding, which for each feature maps every distinct value of that column to its own feature which takes a value of 1 when the categorical feature is equal to that value, and 0 otherwise.
- Oddly distributed data: Although for non-linear models like Gradient Boosted Trees, this has very limited implications, parametric models like regression can produce wildly inaccurate estimates when fed highly skewed data. In some cases, simply taking the natural log of the features is sufficient to produce more normally distributed data. In others, bucketing values into discrete ranges is helpful. These buckets can then be treated as categorical variables and included in the model when one hot encoded.
- Handling more complicated data types: Mainpulating images, text, or data at varying grains is left for other notebook templates.

Luckily, some of these aspects have already been handled for us, and the algorithm we are showcasing tends to do well at handling sparse or oddly distributed data. Therefore, let's keep pre-processing simple.

In [10]:
```
data['no_previous_contact'] = np.where(data['pdays'] == 999, 1, 0)                                  # Indicator variable
data['not_working'] = np.where(np.in1d(data['job'], ['student', 'retired', 'unemployed']), 1, 0)    # Indicator for indi
model_data = pd.get_dummies(data)                                                                   # Convert categorica
```

Another question to ask yourself before building a model is whether certain features will add value in your final use case. For example, if your goal is to deliver the best prediction, then will you have access to that data at the moment of prediction? Knowing it's raining is highly predictive for umbrella sales, but forecasting weather far enough out to plan inventory on umbrellas is probably just as difficult as forecasting umbrella sales without knowledge of the weather. So, including this in your model may give you a false sense of precision.

Following this logic, let's remove the economic features and `duration` from our data as they would need to be forecasted with high precision to use as inputs in future predictions.

Even if we were to use values of the economic indicators from the previous quarter, this value is likely not as relevant for prospects contacted early in the next quarter as those contacted later on.

In [8]:
```
model_data = model_data.drop(['duration', 'emp.var.rate', 'cons.price.idx', 'cons.conf.idx', 'euribor3m', 'nr.employed'
```

When building a model whose primary goal is to predict a target value on new data, it is important to understand overfitting. Supervised learning models are designed to minimize error between their predictions of the target value and actuals, in the data they are given. This last part is key, as frequently in their quest for greater accuracy, machine learning models bias themselves toward picking up on minor idiosyncrasies within the data they are shown. These idiosyncrasies then don't repeat themselves in subsequent data, meaning those predictions can actually be made less accurate, at the expense of more accurate predictions

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The most common way of preventing this is to build models with the concept that a model shouldn't only be judged on its fit to the data it was trained on, but also on "new" data. There are several different ways of operationalizing this, holdout validation, cross-validation, leave-one-out validation, etc. For our purposes, we'll simply randomly split the data into 3 uneven groups. The model will be trained on 70% of data, it will then be evaluated on 20% of data to give us an estimate of the accuracy we hope to have on "new" data, and 10% will be held back as a final testing dataset which will be used later on.

In [9]:
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```

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```

Training

Now we know most of our features have skewed distributions, some are highly correlated with one another, and some appear to have non-linear relationships with our target variable. Also, for targeting future prospects, good predictive accuracy is preferred to being able to explain why that prospect was targeted. Taken together, these aspects make gradient boosted trees a good candidate algorithm.

There are several intricacies to understanding the algorithm, but at a high level, gradient boosted trees works by combining predictions from many simple models, each of which tries to address the weaknesses of the previous models. By doing this the collection of simple models can actually outperform large, complex models. Other Amazon SageMaker notebooks elaborate on gradient boosting trees further and how they differ from similar algorithms.

`xgboost` is an extremely popular, open-source package for gradient boosted trees. It is computationally powerful, fully featured, and has been successfully used in many machine learning competitions. Let's start with a simple `xgboost` model, trained using Amazon SageMaker's managed, distributed training framework.

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In [21]:
```
dump_svmlight_file(X=train_data.drop(['y_no', 'y_yes'], axis=1), y=train_data['y_yes'], f='train.libsvm')
dump_svmlight_file(X=validation_data.drop(['y_no', 'y_yes'], axis=1), y=validation_data['y_yes'], f='validation.libsvm'
dump_svmlight_file(X=test_data.drop(['y_no', 'y_yes'], axis=1), y=test_data['y_yes'], f='test.libsvm')
```

Now we'll copy the file to S3 for Amazon SageMaker's managed training to pickup.

In [22]:
```
boto3.Session().resource('s3').Bucket(bucket).Object(os.path.join(prefix, 'train/train.libsvm')).upload_file('train.lib
boto3.Session().resource('s3').Bucket(bucket).Object(os.path.join(prefix, 'train/validation.libsvm')).upload_file('vali
boto3.Session().resource('s3').Bucket(bucket).Object(os.path.join(prefix, 'train/test.libsvm')).upload_file('test.libsv
```

Training

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First we'll need to specify training parameters. This includes:

1. The role to use
2. Our training job name
3. The `xgboost` algorithm container
4. Training instance type and count
5. S3 location for training data
6. S3 location for output data
7. Algorithm hyperparameters
8. Stopping conditions

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Training

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5. S3 location for training data
6. S3 location for output data
7. Algorithm hyperparameters
8. Stopping conditions

In [ ]:

```
job_name = 'xgboost-dm-' + strftime("%Y-%m-%d-%H-%M-%S", gmtime())
print("Training job", job_name)

create_training_params = \
{
    "RoleArn": role,
    "TrainingJobName": job_name,
    "AlgorithmSpecification": {
        "TrainingImage": "032969728358.dkr.ecr.us-west-2.amazonaws.com/xgboost-learner:latest",
        "TrainingInputMode": "File"
    },
```

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Training

Now we know most of our features have skewed distributions, some are highly correlated with one another, and some appear to have non-linear relationships with our target variable. Also, for targeting future prospects, good predictive accuracy is preferred to being able to explain why that prospect was targeted. Taken together, these aspects make gradient boosted trees a good candidate algorithm.

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{
    "RoleArn": role,
    "TrainingJobName": job_name,
    "AlgorithmSpecification": {
        "TrainingImage": "032969728358.dkr.ecr.us-west-2.amazonaws.com/xgboost-learner:latest",
        "TrainingInputMode": "File"
    },
```

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3. The `xgboost` algorithm container
4. Training instance type and count
5. S3 location for training data
6. S3 location for output data
7. Algorithm hyperparameters
8. Stopping conditions

In [ ]:

```
job_name = 'xgboost-dm-' + strftime("%Y-%m-%d-%H-%M-%S", gmtime())
print("Training job", job_name)

create_training_params = \
{
    "RoleArn": role,
    "TrainingJobName": job_name,
    "AlgorithmSpecification": {
        "TrainingImage": "032969728358.dkr.ecr.us-west-2.amazonaws.com/xgboost-learner:latest",
        "TrainingInputMode": "File"
    },
    "ResourceConfig": {
        "InstanceCount": 2,
        "InstanceType": "ml.c4.2xlarge",
        "VolumeSizeInGB": 50
    },
    "InputDataConfig": [
        {
            "ChannelName": "train",
            "DataSource": {
                "S3DataSource": {
                    "S3DataType": "S3Prefix",
                    "S3Uri": "s3://{}/{}/train".format(bucket, prefix),
                    "S3DataDistributionType": "FullyReplicated"
                }
            },
            "ContentType": "libsvm",
            "CompressionType": "None"
        }
    ],
    "OutputDataConfig": {
        "S3OutputPath": "s3://{}/{}/output".format(bucket, prefix)
    },
    "HyperParameters": {
```

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    "TrainingJobName": job_name,
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        "TrainingInputMode": "File"
    },
    "ResourceConfig": {
        "InstanceCount": 2,
        "InstanceType": "ml.c4.2xlarge",
        "VolumeSizeInGB": 50
    },
    "InputDataConfig": [
        {
            "ChannelName": "train",
            "DataSource": {
                "S3DataSource": {
                    "S3DataType": "S3Prefix",
                    "S3Uri": "s3://{}/{}/train".format(bucket, prefix),
                    "S3DataDistributionType": "FullyReplicated"
                }
            },
            "ContentType": "libsvm",
            "CompressionType": "None"
        }
    ],
    "OutputDataConfig": {
        "S3OutputPath": "s3://{}/{}/output".format(bucket, prefix)
    },
    "HyperParameters": {
        "max_depth":"5",
        "eta":"0.2",
        "gamma":"4",
        "min_child_weight":"6",
        "subsample":"0.8",
        "silent":"0",
        "objective":"binary:logistic",
        "num_class":"1",
```

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In [ ]:
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    "TrainingJobName": job_name,
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        "TrainingImage": "032969728358.dkr.ecr.us-west-2.amazonaws.com/xgboost-learner:latest",
        "TrainingInputMode": "File"
    },
    "ResourceConfig": {
        "InstanceCount": 2,
        "InstanceType": "ml.c4.2xlarge",
        "VolumeSizeInGB": 50
    },
    "InputDataConfig": [
        {
            "ChannelName": "train",
            "DataSource": {
                "S3DataSource": {
                    "S3DataType": "S3Prefix",
                    "S3Uri": "s3://{}/{}/train".format(bucket, prefix),
                    "S3DataDistributionType": "FullyReplicated"
                }
            },
            "ContentType": "libsvm",
            "CompressionType": "None"
        }
    ],
    "OutputDataConfig": {
        "S3OutputPath": "s3://{}/{}/output".format(bucket, prefix)
    },
    "HyperParameters": {
        "max_depth":"5",
        "eta":"0.2",
        "gamma":"4",
        "min_child_weight":"6",
        "subsample":"0.8",
        "silent":"0",
        "objective":"binary:logistic",
        "num_class":"1",
```

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```
                "ContentType": "libsvm",
                "CompressionType": "None"
            }
        ],
        "OutputDataConfig": {
            "S3OutputPath": "s3://{}/{}/output".format(bucket, prefix)
        },
        "HyperParameters": {
            "max_depth":"5",
            "eta":"0.2",
            "gamma":"4",
            "min_child_weight":"6",
            "subsample":"0.8",
            "silent":"0",
            "objective":"binary:logistic",
            "num_class":"1",
            "num_round":"100",
            "train_file_name":"train.libsvm",
            "val_file_name":"validation.libsvm"
        },
        "StoppingCondition": {
            "MaxRuntimeInSeconds": 60 * 60
        }
}
```

In [ ]:

```
client = boto3.client('sagemaker')
client.create_training_job(**create_training_params)

status = client.describe_training_job(TrainingJobName=job_name)['TrainingJobStatus']
print(status)
client.get_waiter('TrainingJob_Created').wait(TrainingJobName=job_name)
status = client.describe_training_job(TrainingJobName=job_name)['TrainingJobStatus']
print("Training job ended with status: " + status)
if status == 'Failed':
    message = client.describe_training_job(TrainingJobName=job_name)['FailureReason']
    print('Training failed with the following error: {}'.format(message))
    raise Exception('Training job failed')
```

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```
        "max_depth":"5",
        "eta":"0.2",
        "gamma":"4",
        "min_child_weight":"6",
        "subsample":"0.8",
        "silent":"0",
        "objective":"binary:logistic",
        "num_class":"1",
        "num_round":"100",
        "train_file_name":"train.libsvm",
        "val_file_name":"validation.libsvm"
    },
    "StoppingCondition": {
        "MaxRuntimeInSeconds": 60 * 60
    }
}
```

In [ ]:

```
client = boto3.client('sagemaker')
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status = client.describe_training_job(TrainingJobName=job_name)['TrainingJobStatus']
print(status)
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    print('Training failed with the following error: {}'.format(message))
    raise Exception('Training job failed')
```

Hosting

Now that we've trained the `xgboost` algorithm on our data, let's setup a model which can later be hosted.

In [ ]:

```
primary_container = {
    'Image': "032969728358.dkr.ecr.us-west-2.amazonaws.com/xgboost-learner:latest",
    'ModelDataUrl': client.describe_training_job(TrainingJobName=job_name)['ModelArtifacts']['S3ModelArtifacts']
}
```

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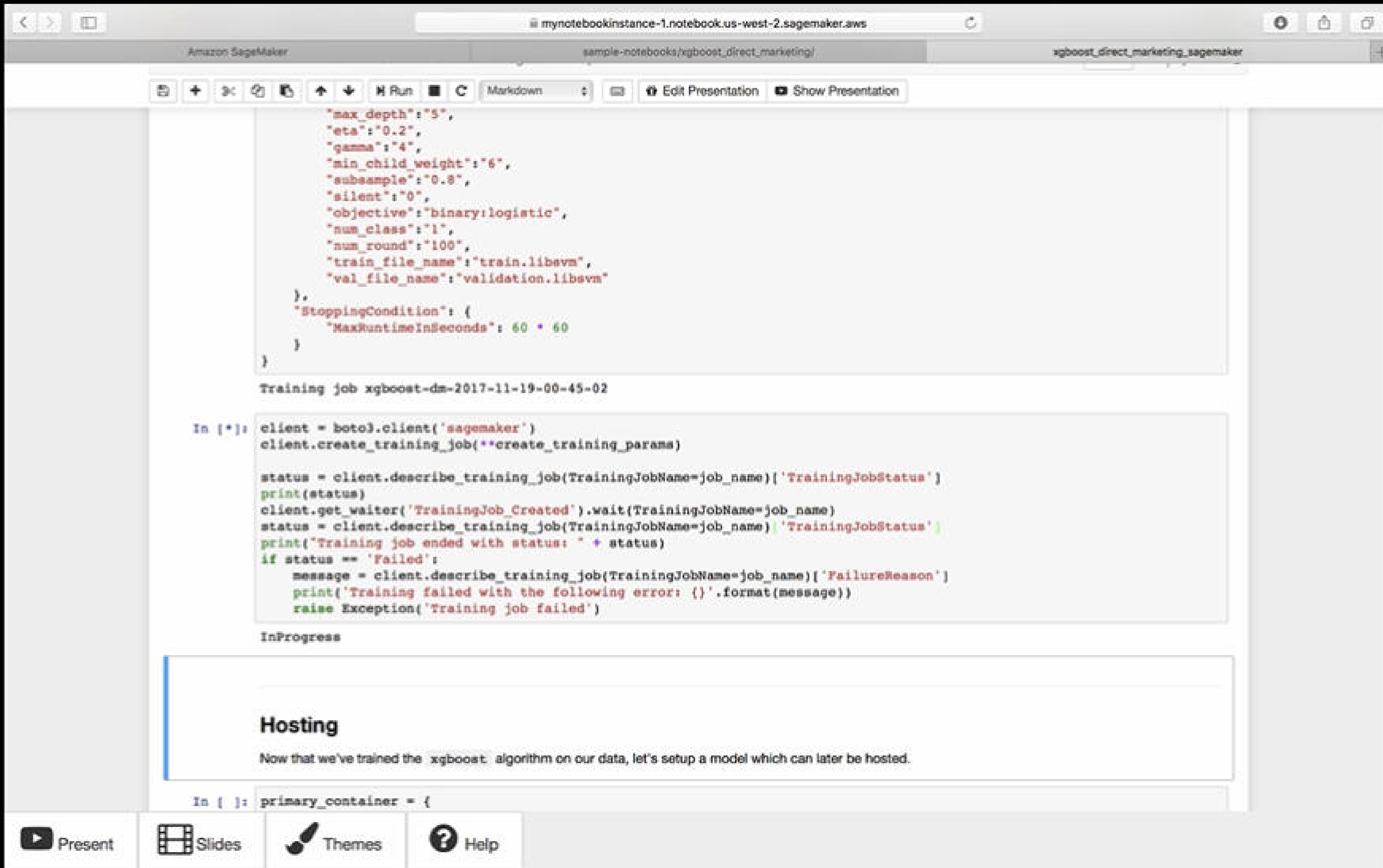
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"max_depth":"5",
"eta":"0.2",
"gamma":"4",
"min_child_weight":"6",
"subsample":"0.8",
"silent":"0",
"objective":"binary:logistic",
"num_class":"1",
"num_round":"100",
"train_file_name":"train.libsvm",
"val_file_name":"validation.libsvm"
},
"StoppingCondition": {
"MaxRuntimeInSeconds": 60 * 60
}
}
Training job xgboost-dm-2017-11-19-00-45-02
In [*]:
client = boto3.client('sagemaker')
client.create_training_job(**create_training_params)
status = client.describe_training_job(TrainingJobName=job_name)['TrainingJobStatus']
print(status)
client.get_waiter('TrainingJob_Created').wait(TrainingJobName=job_name)
status = client.describe_training_job(TrainingJobName=job_name)['TrainingJobStatus']
print("Training job ended with status: " + status)
if status == 'Failed':
message = client.describe_training_job(TrainingJobName=job_name)['FailureReason']
print('Training failed with the following error: {}'.format(message))
raise Exception('Training job failed')
InProgress
Hosting
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In [ ]:
primary_container = {
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```
            "eta":"0.2",
            "gamma":"4",
            "min_child_weight":"6",
            "subsample":"0.8",
            "silent":"0",
            "objective":"binary:logistic",
            "num_class":"1",
            "num_round":"100",
            "train_file_name":"train.libsvm",
            "val_file_name":"validation.libsvm"
        },
        "StoppingCondition": {
            "MaxRuntimeInSeconds": 60 * 60
        }
}
```

```
Training job xgboost-dm-2017-11-19-00-45-02
```

In [24]:

```
client = boto3.client('sagemaker')
client.create_training_job(**create_training_params)

status = client.describe_training_job(TrainingJobName=job_name)['TrainingJobStatus']
print(status)
client.get_waiter('TrainingJob_Created').wait(TrainingJobName=job_name)
status = client.describe_training_job(TrainingJobName=job_name)['TrainingJobStatus']
print("Training job ended with status: " + status)
if status == 'Failed':
    message = client.describe_training_job(TrainingJobName=job_name)['FailureReason']
    print('Training failed with the following error: {}'.format(message))
    raise Exception('Training job failed')
```

```
InProgress
Training job ended with status: Completed
```

Hosting

Now that we've trained the `xgboost` algorithm on our data, let's setup a model which can later be hosted.

In [ ]:

```
primary_container = {
```

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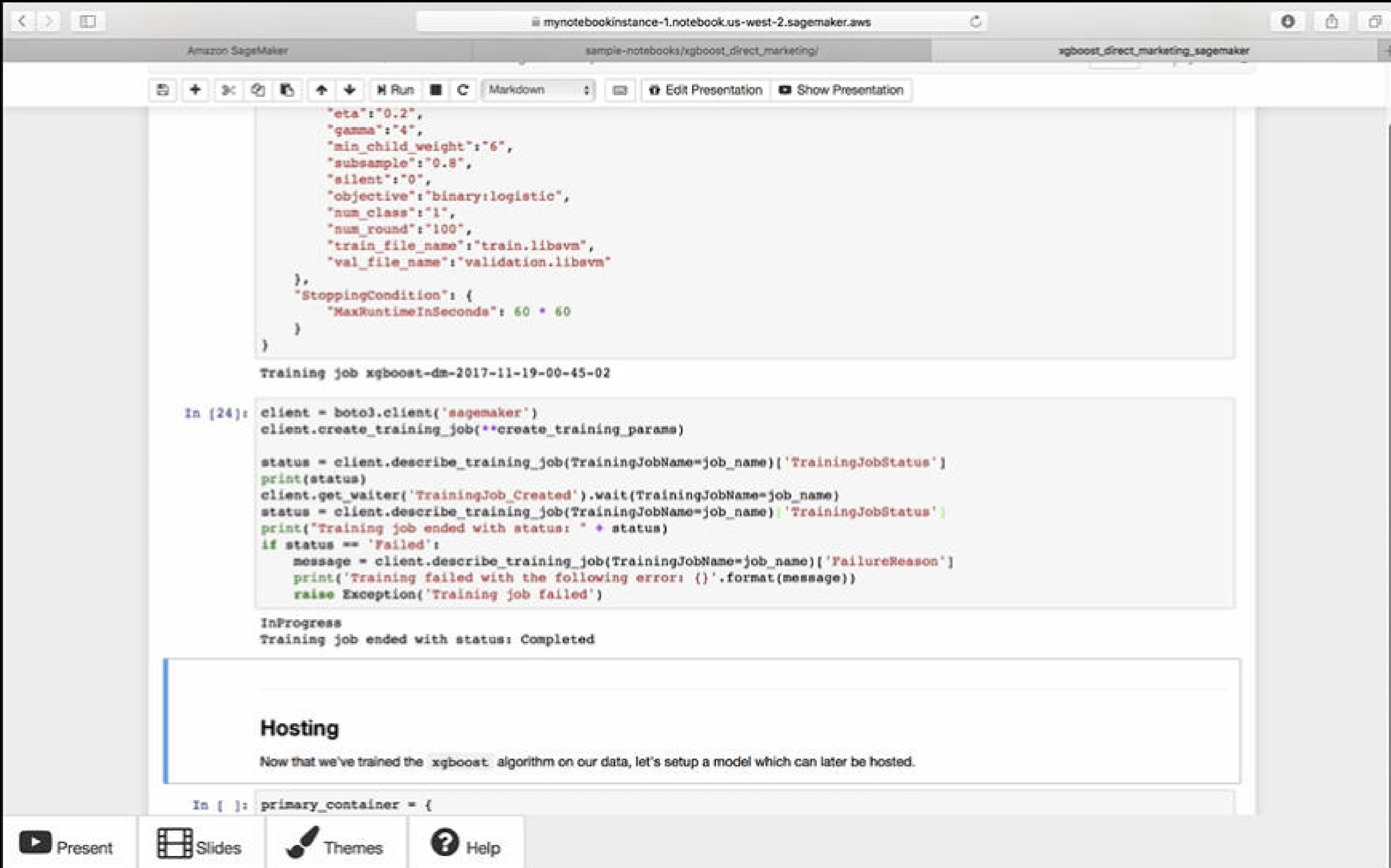
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"eta":"0.2",
"gamma":"4",
"min_child_weight":"6",
"subsample":"0.8",
"silent":"0",
"objective":"binary:logistic",
"num_class":"1",
"num_round":"100",
"train_file_name":"train.libsvm",
"val_file_name":"validation.libsvm"
},
"StoppingCondition": {
"MaxRuntimeInSeconds": 60 * 60
}
}
Training job xgboost-dm-2017-11-19-00-45-02
In [24]:
client = boto3.client('sagemaker')
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InProgress
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Hosting
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primary_container = {
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Hosting

Now that we've trained the `xgboost` algorithm on our data, let's setup a model which can later be hosted.

In [ ]:

```
primary_container = {
    'Image': '032969728358.dkr.ecr.us-west-2.amazonaws.com/xgboost-learner:latest',
    'ModelDataUrl': client.describe_training_job(TrainingJobName=job_name)['ModelArtifacts']['S3ModelArtifacts']
}

create_model_response = client.create_model(
    ModelName = job_name,
    ExecutionRoleArn = role,
    PrimaryContainer = primary_container)

print(create_model_response['ModelArn'])
```

In [ ]:

```
endpoint_config_name = 'xgboost-endpoint-config-' + strftime("%Y-%m-%d-%H-%M-%S", gmtime())
print(endpoint_config_name)
create_endpoint_config_response = client.create_endpoint_config(
    EndpointConfigName = endpoint_config_name,
    ProductionVariants=[{
        'InstanceType': 'ml.c4.xlarge',
        'InitialInstanceCount': 1,
        'ModelName': job_name,
        'VariantName': 'AllTraffic'}])

print("Endpoint Config Arn: " + create_endpoint_config_response['EndpointConfigArn'])
```

Now that we've specified how our endpoint should be configured, we can create them. This can be done in the background, but for now let's run a loop that updates us on the status of the endpoints so that we know when they are ready for use.

In [ ]:

```
endpoint_name = 'xgboost-endpoint-' + strftime("%Y-%m-%d-%H-%M-%S", gmtime())
print(endpoint_name)
create_endpoint_response = client.create_endpoint(
    EndpointName=endpoint_name,
    EndpointConfigName=endpoint_config_name)
print(create_endpoint_response['EndpointArn'])
```

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Hosting

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In [25]:

```
primary_container = {
    'Image': '032969728358.dkr.ecr.us-west-2.amazonaws.com/xgboost-learner:latest',
    'ModelDataUrl': client.describe_training_job(TrainingJobName=job_name)['ModelArtifacts']['S3ModelArtifacts']
}

create_model_response = client.create_model(
    ModelName = job_name,
    ExecutionRoleArn = role,
    PrimaryContainer = primary_container)

print(create_model_response['ModelArn'])
```

```
arn:aws:sagemaker:us-west-2:811689727410:model/xgboost-dm-2017-11-19-00-45-02
```

In [ ]:

```
endpoint_config_name = 'xgboost-endpoint-config-' + strftime("%Y-%m-%d-%H-%M-%S", gmtime())
print(endpoint_config_name)
create_endpoint_config_response = client.create_endpoint_config(
    EndpointConfigName = endpoint_config_name,
    ProductionVariants=[{
        'InstanceType': 'ml.c4.xlarge',
        'InitialInstanceCount': 1,
        'ModelName': job_name,
        'VariantName': 'AllTraffic'}])

print("Endpoint Config Arn: " + create_endpoint_config_response['EndpointConfigArn'])
```

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```
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print(endpoint_name)
create_endpoint_response = client.create_endpoint(
    EndpointName=endpoint_name,
```

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    'ModelDataUrl': client.describe_training_job(TrainingJobName=job_name)['ModelArtifacts']['S3ModelArtifacts']
}

create_model_response = client.create_model(
    ModelName = job_name,
    ExecutionRoleArn = role,
    PrimaryContainer = primary_container)

print(create_model_response['ModelArn'])
```

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create_endpoint_config_response = client.create_endpoint_config(
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    ProductionVariants=[{
        'InstanceType': 'ml.c4.xlarge',
        'InitialInstanceCount': 1,
        'ModelName': job_name,
        'VariantName': 'AllTraffic'}])

print("Endpoint Config Arn: " + create_endpoint_config_response['EndpointConfigArn'])
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endpoint_name = 'xgboost-endpoint-' + strftime("%Y-%m-%d-%H-%M-%S", gmtime())
print(endpoint_name)
create_endpoint_response = client.create_endpoint(
    EndpointName=endpoint_name,
```

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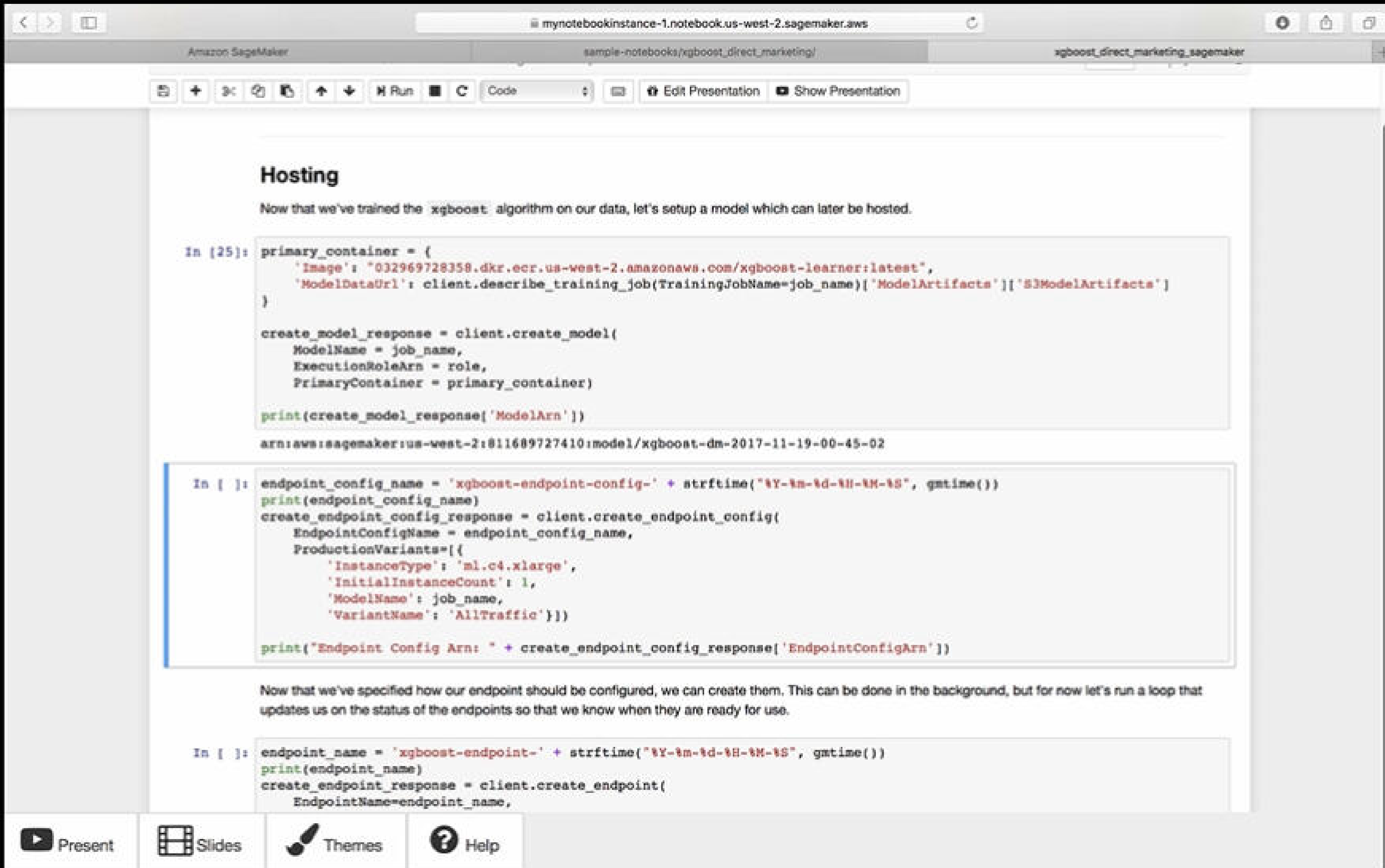
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Amazon SageMaker
sample-notebooks/xgboost_direct_marketing/
xgboost_direct_marketing_sagemaker
Run
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Hosting
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primary_container = {
'Image': '032969728358.dkr.ecr.us-west-2.amazonaws.com/xgboost-learner:latest',
'ModelDataUrl': client.describe_training_job(TrainingJobName=job_name)['ModelArtifacts']['S3ModelArtifacts']
}
create_model_response = client.create_model(
ModelName = job_name,
ExecutionRoleArn = role,
PrimaryContainer = primary_container)
print(create_model_response['ModelArn'])
arn:aws:sagemaker:us-west-2:811689727410:model/xgboost-dm-2017-11-19-00-45-02
In [ ]:
endpoint_config_name = 'xgboost-endpoint-config-' + strftime("%Y-%m-%d-%H-%M-%S", gmtime())
print(endpoint_config_name)
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EndpointConfigName = endpoint_config_name,
ProductionVariants=[{
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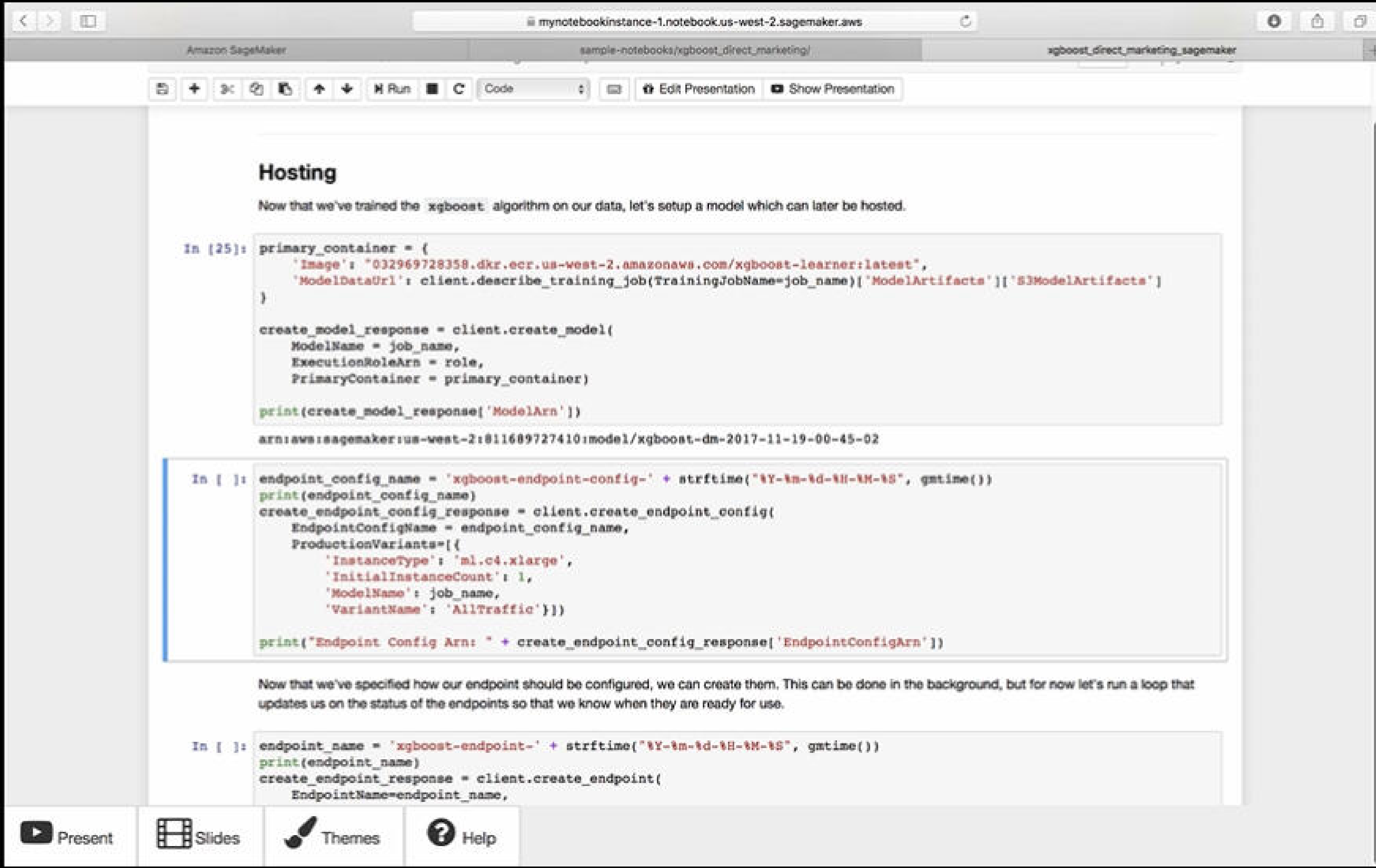

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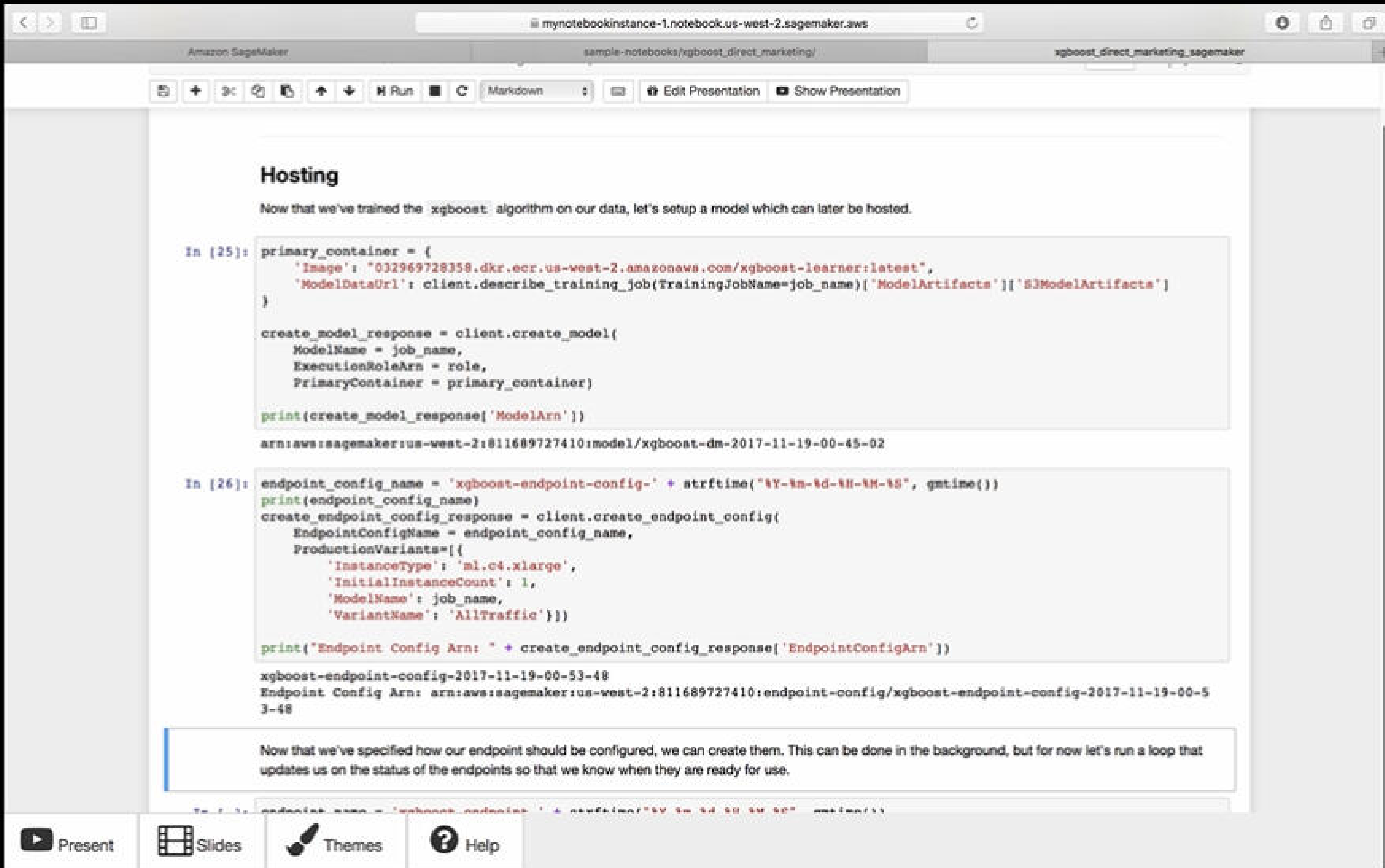

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arn:aws:sagemaker:us-west-2:811689727410:model/xgboost-dm-2017-11-19-00-45-02
In [26]:
endpoint_config_name = 'xgboost-endpoint-config-' + strftime("%Y-%m-%d-%H-%M-%S", gmtime())
print(endpoint_config_name)
create_endpoint_config_response = client.create_endpoint_config(
EndpointConfigName = endpoint_config_name,
ProductionVariants=[{
'InstanceType': 'ml.c4.xlarge',
'InitialInstanceCount': 1,
'ModelName': job_name,
'VariantName': 'AllTraffic'}])
print("Endpoint Config Arn: " + create_endpoint_config_response['EndpointConfigArn'])
xgboost-endpoint-config-2017-11-19-00-53-48
Endpoint Config Arn: arn:aws:sagemaker:us-west-2:811689727410:endpoint-config/xgboost-endpoint-config-2017-11-19-00-5
3-48
Now that we've specified how our endpoint should be configured, we can create them. This can be done in the background, but for now let's run a loop that updates us on the status of the endpoints so that we know when they are ready for use.
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print(create_model_response['ModelArn'])
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print("Endpoint Config Arn: " + create_endpoint_config_response['EndpointConfigArn'])
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Hosting

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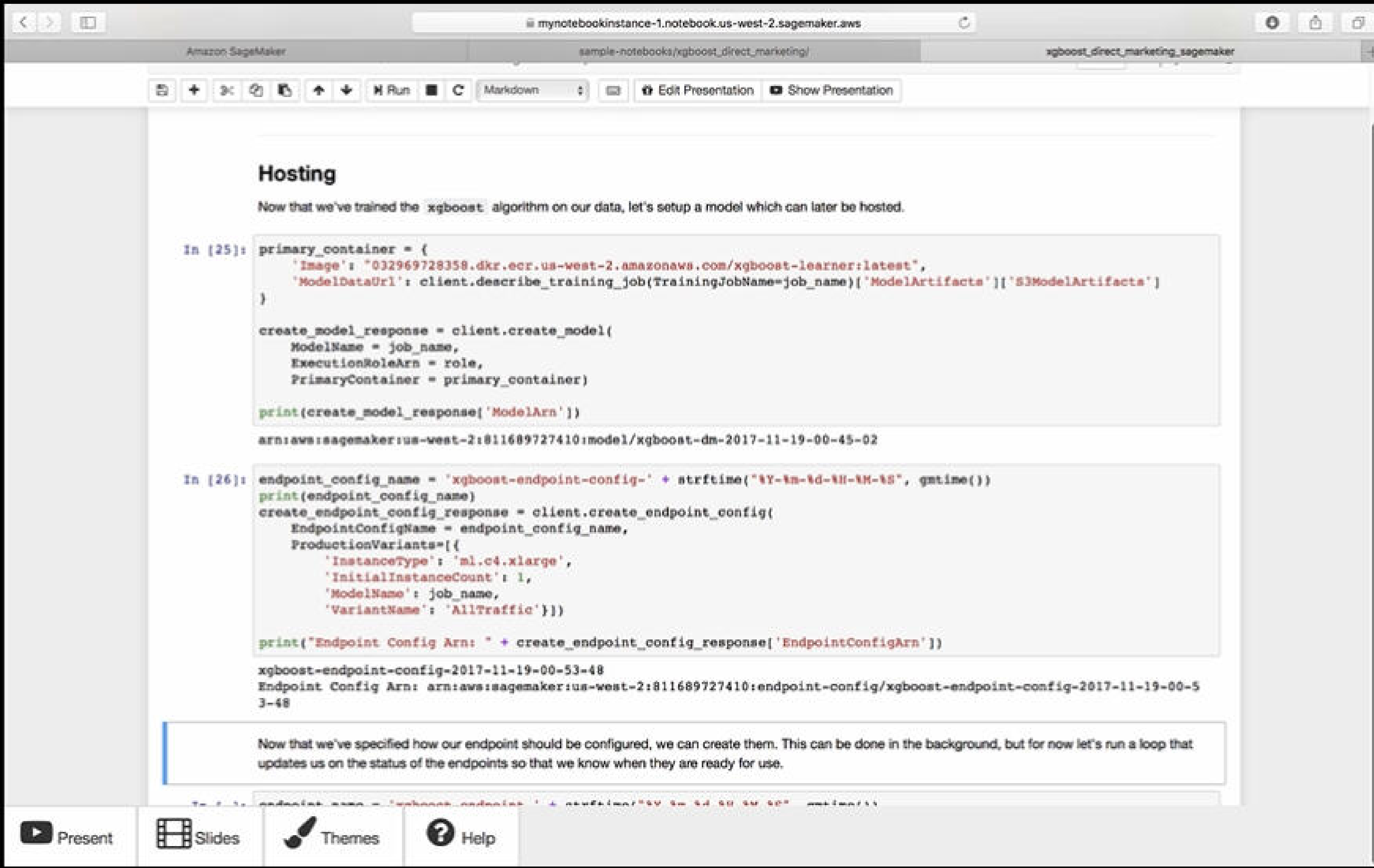
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Evaluation

There are many ways to compare the performance of a machine learning model, but let's start by simply by comparing actual to predicted values. In this case, we're simply predicting whether the customer subscribed to a term deposit (`1`) or not (`0`), which produces a simple confusion matrix.

In [28]:
```
runtime = boto3.client('sagemaker-runtime')
```

In [29]:
```
def do_predict(data, endpoint_name, content_type):
    payload = '\n'.join(data)
    response = runtime.invoke_endpoint(EndpointName=endpoint_name,
                                       ContentType=content_type,
                                       Body=payload)
    result = response['Body'].read()
    result = result.decode("utf-8")
    result = result.split(',')
    preds = [float((num)) for num in result]
    preds = [round(num) for num in preds]
    return preds

def batch_predict(data, batch_size, endpoint_name, content_type):
    items = len(data)
    arrs = []

    for offset in range(0, items, batch_size):
        if offset+batch_size < items:
            results = do_predict(data[offset:(offset+batch_size)], endpoint_name, content_type)
            arrs.extend(results)
        else:
            arrs.extend(do_predict(data[offset:items], endpoint_name, content_type))
        sys.stdout.write('.')
    return(arrs)
```

In [ ]:
```
%%time
import json

with open('test.libsvm', 'r') as f:
    payload = f.read().strip()

labels = [int(line.split(' ')[0]) for line in payload.split('\n')]
test_data = [line for line in payload.split('\n')]
preds = batch_predict(test_data, 1000, endpoint_name, 'text/x-libsvm')
```

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```python
                                   Body=payload)
    result = response['Body'].read()
    result = result.decode("utf-8")
    result = result.split(',')
    preds = [float((num)) for num in result]
    preds = [round(num) for num in preds]
    return preds

def batch_predict(data, batch_size, endpoint_name, content_type):
    items = len(data)
    arrs = []

    for offset in range(0, items, batch_size):
        if offset+batch_size < items:
            results = do_predict(data[offset:(offset+batch_size)], endpoint_name, content_type)
            arrs.extend(results)
        else:
            arrs.extend(do_predict(data[offset:items], endpoint_name, content_type))
        sys.stdout.write('.')
    return(arrs)
```

In [34]:

```python
%%time
import json

with open('test.libsvm', 'r') as f:
    payload = f.read().strip()

labels = [int(line.split(' ')[0]) for line in payload.split('\n')]
test_data = [line for line in payload.split('\n')]
preds = batch_predict(test_data, 1000, endpoint_name, 'text/x-libsvm')

print ('\nerror rate=%f' % ( sum(1 for i in range(len(preds)) if preds[i]!=labels[i]) /float(len(preds))))
```

```
.....
error rate=0.095897
CPU times: user 32 ms, sys: 0 ns, total: 32 ms
Wall time: 650 ms
```

In [ ]:

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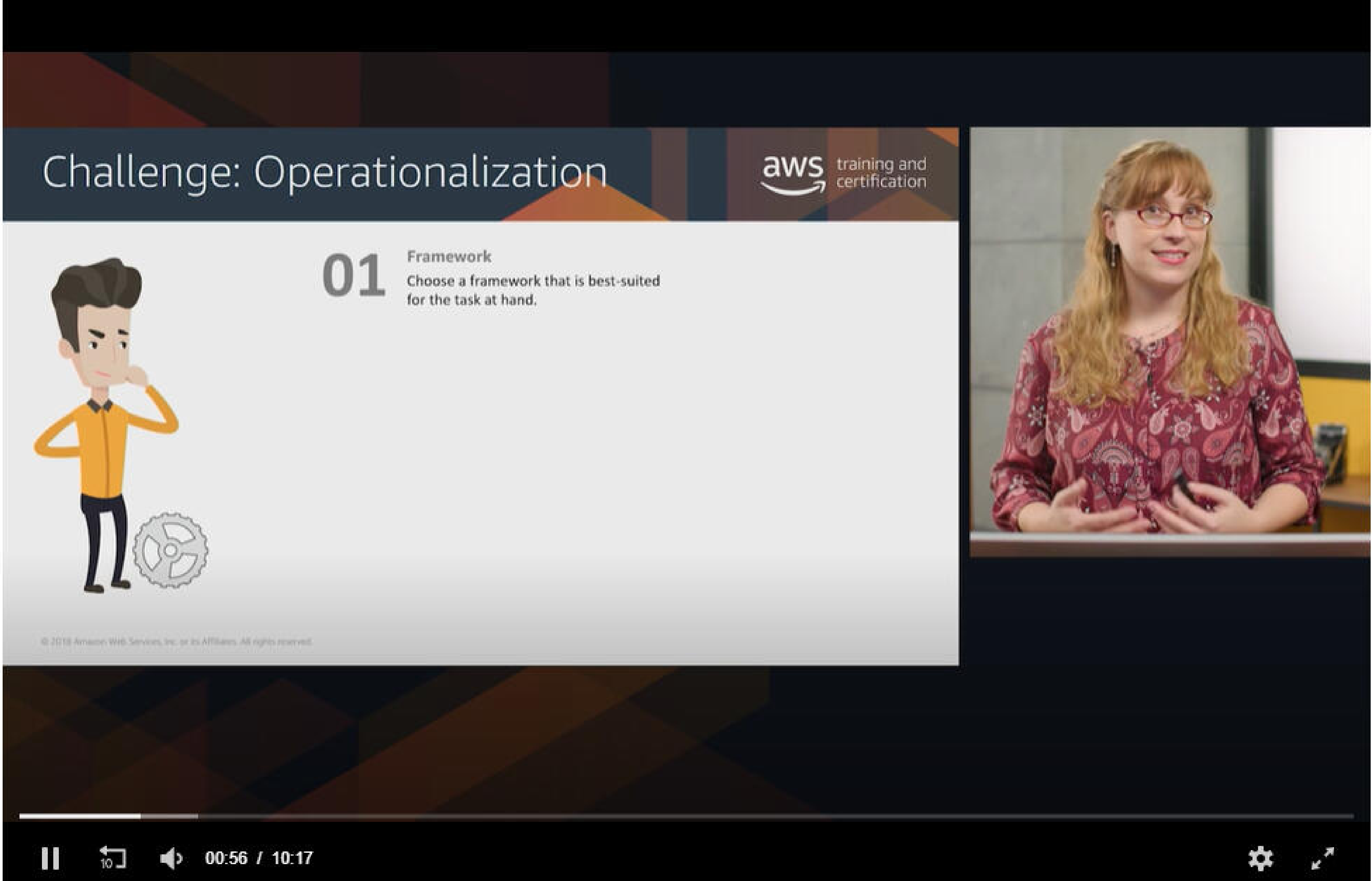
00:41 / 10:17


Challenge: Operationalization
aws training and certification
01
Framework
Choose a framework that is best-suited for the task at hand.
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00:56 / 10:17

Challenge: Operationalization

01 Framework

Choose a framework that is best-suited for the task at hand.

02 Models

Build the models using the chosen framework.

03 Train Models to Make Predictions

Train a model using sample data to make accurate predictions on bigger data sets.

Challenge: Operationalization

01 Framework

Choose a framework that is best-suited for the task at hand.

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Build the models using the chosen framework.

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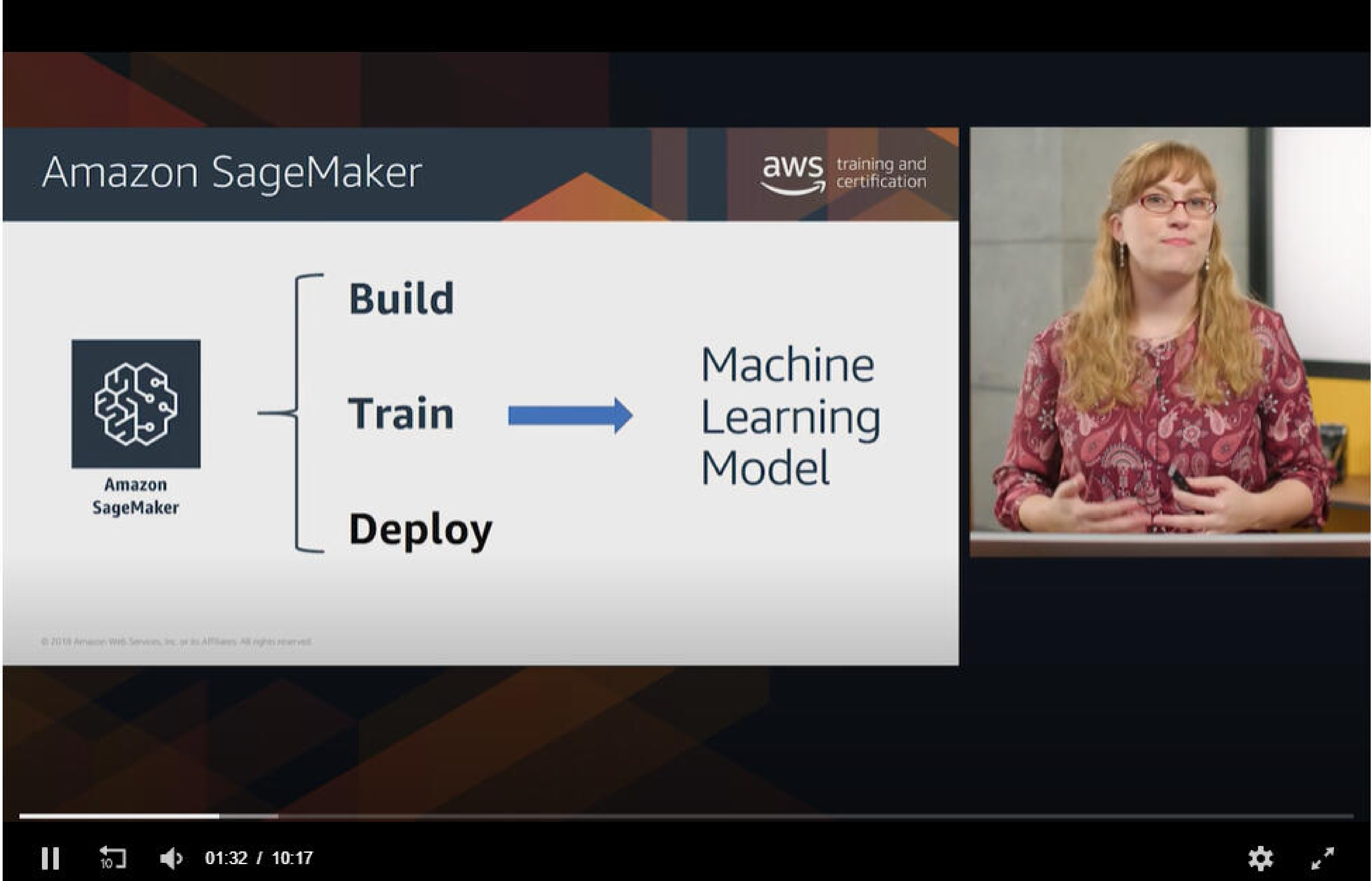
Train a model using sample data to make accurate predictions on bigger data sets.

04 Integrate

Integrate the model with the application.

05 Deploy

Deploy the application, the model, and the framework on a platform.



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Amazon SageMaker
Build
Train
Deploy
Machine Learning Model
01:32 / 10:17

Amazon SageMaker

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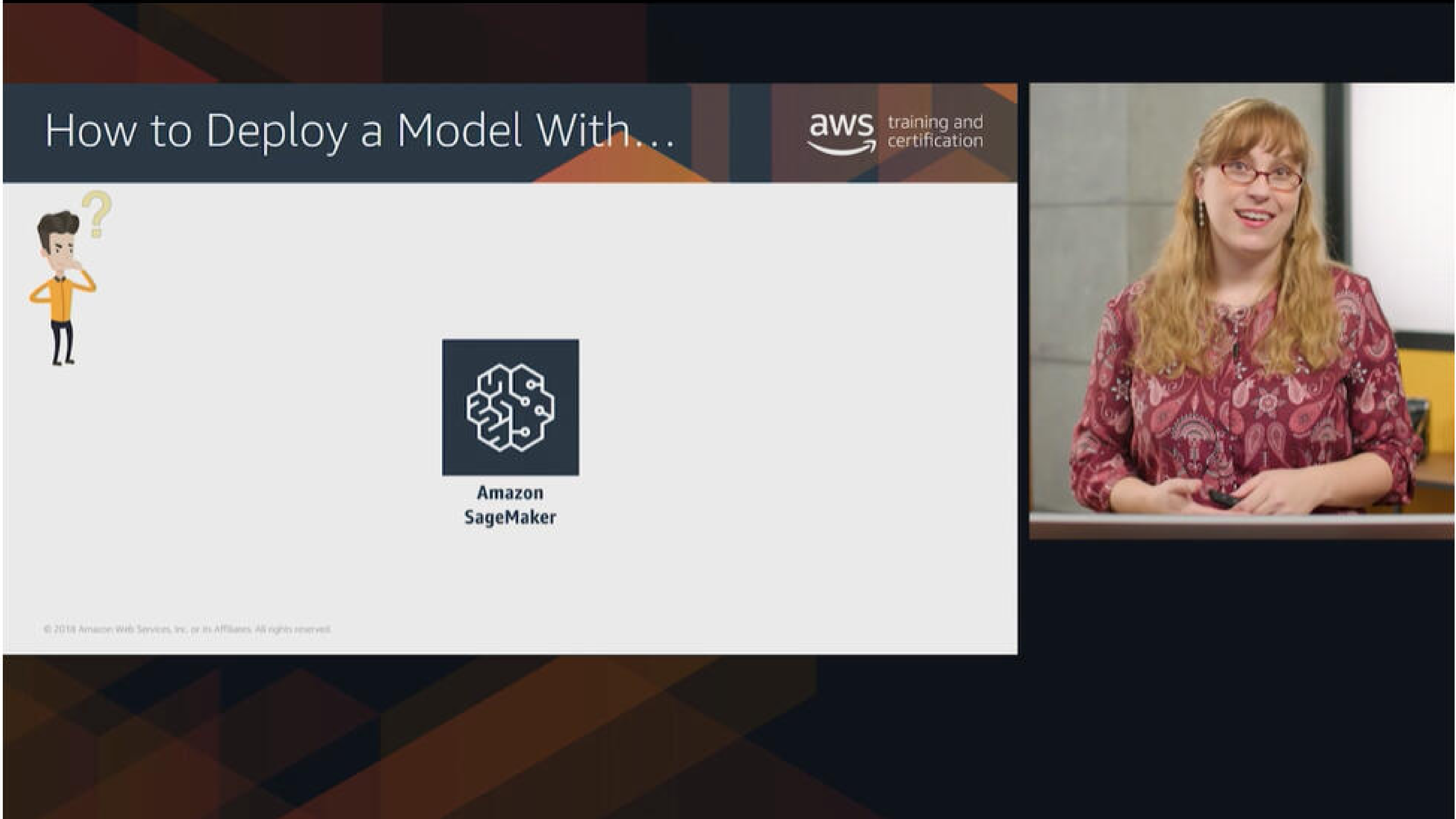
Amazon SageMaker

Build

Train

Deploy

→ Machine Learning Model



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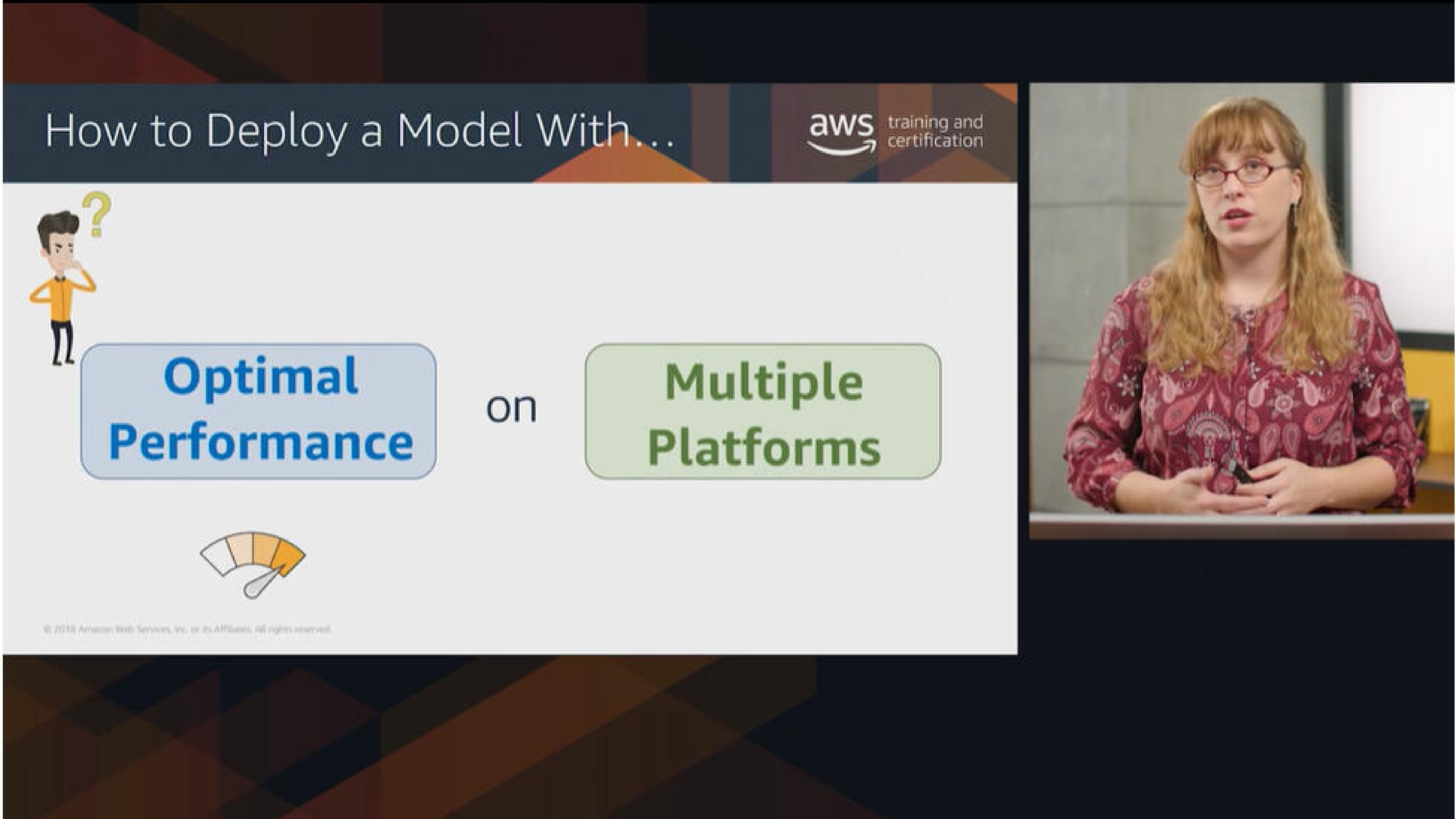
Amazon SageMaker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Optimal Performance
on
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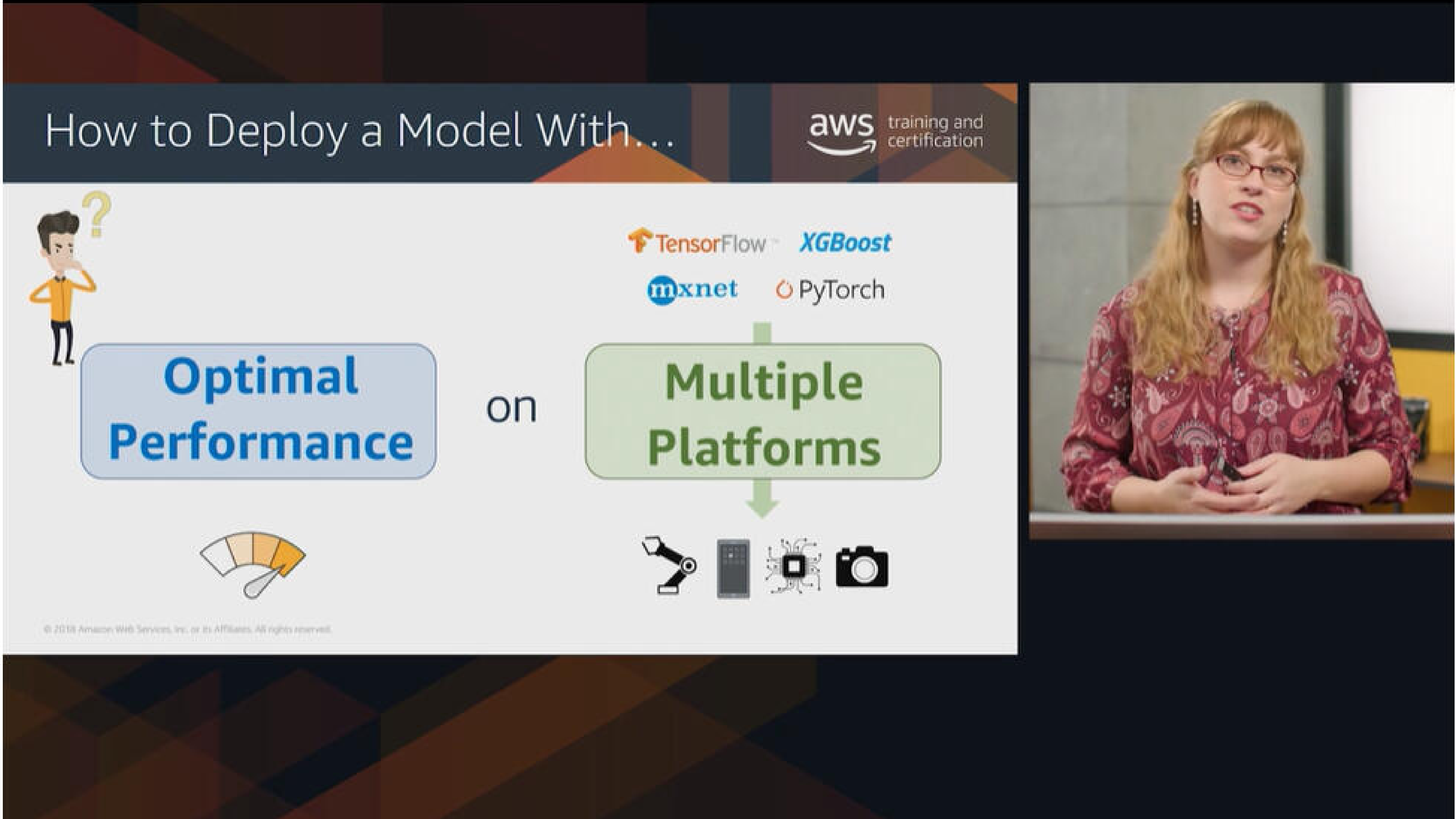
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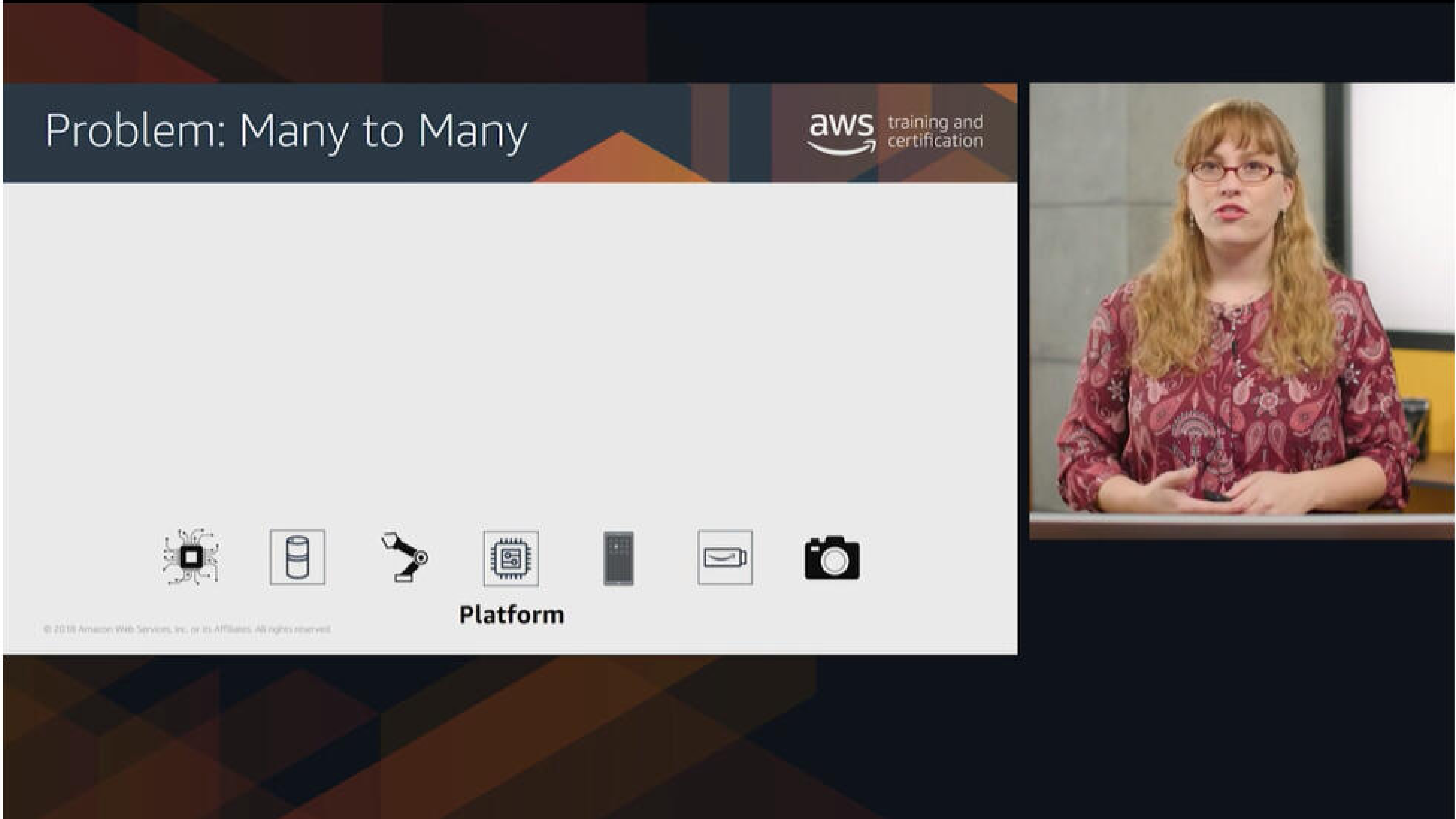
Problem: Many to Many
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Platform
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Problem: Many to Many

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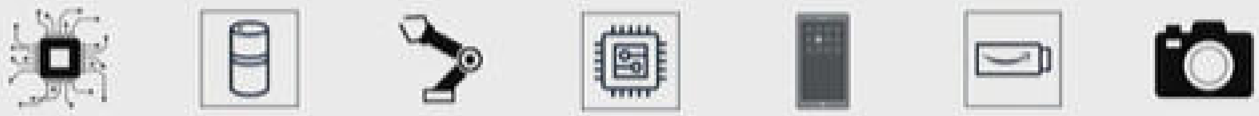
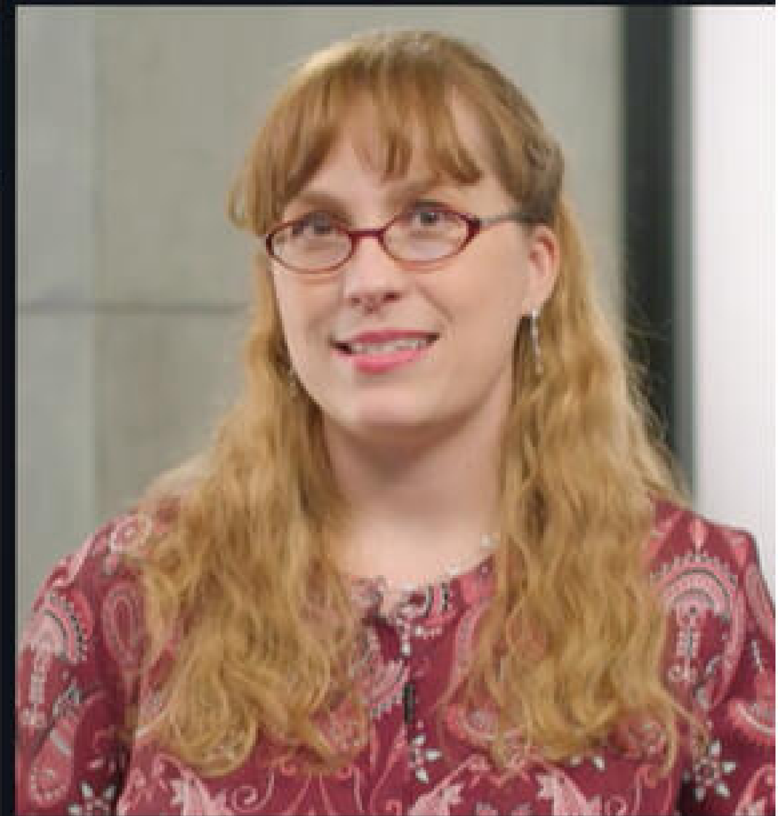
Framework

TensorFlow mxnet PYTORCH XGBoost



Platform



Problem: Many to Many

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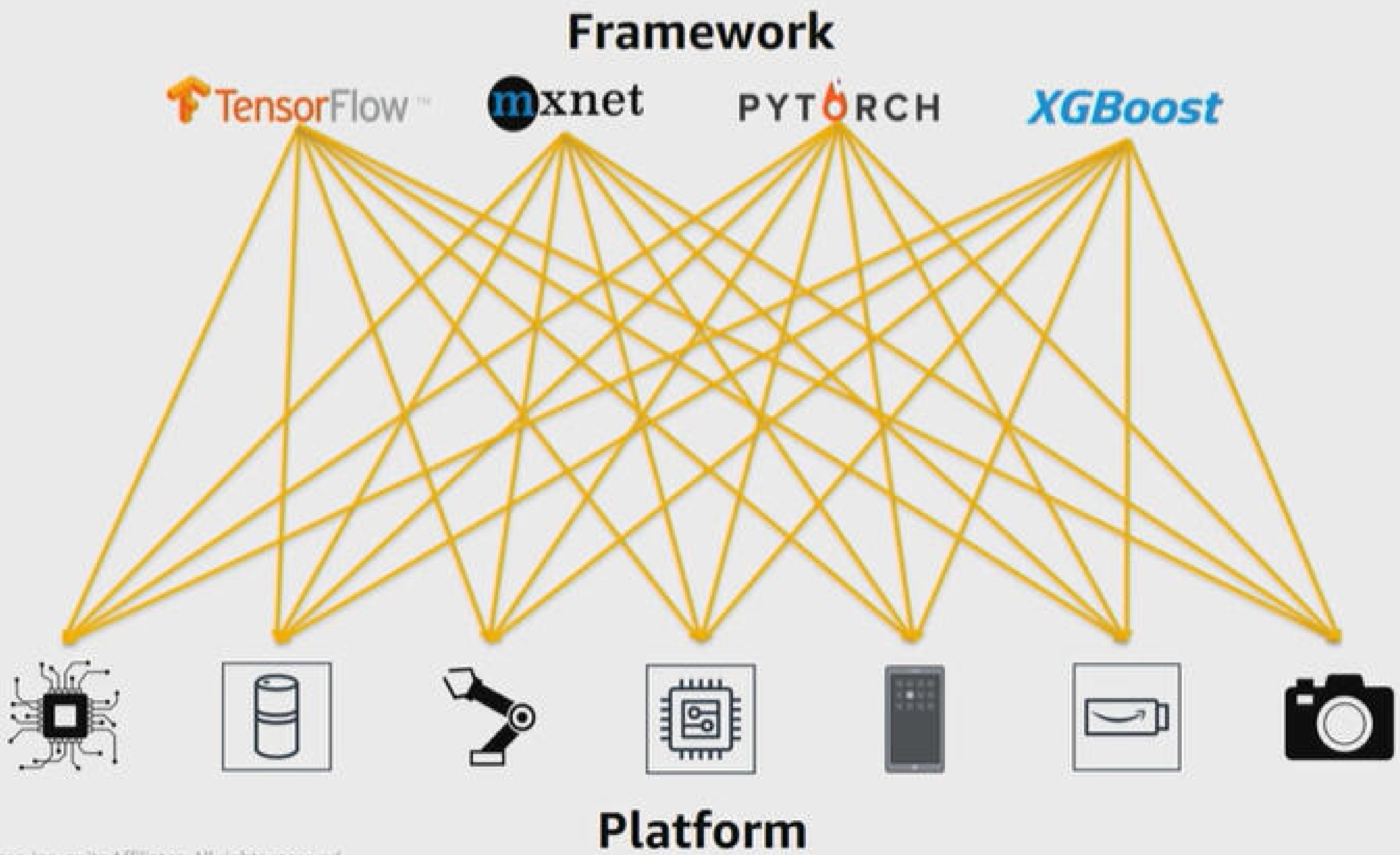

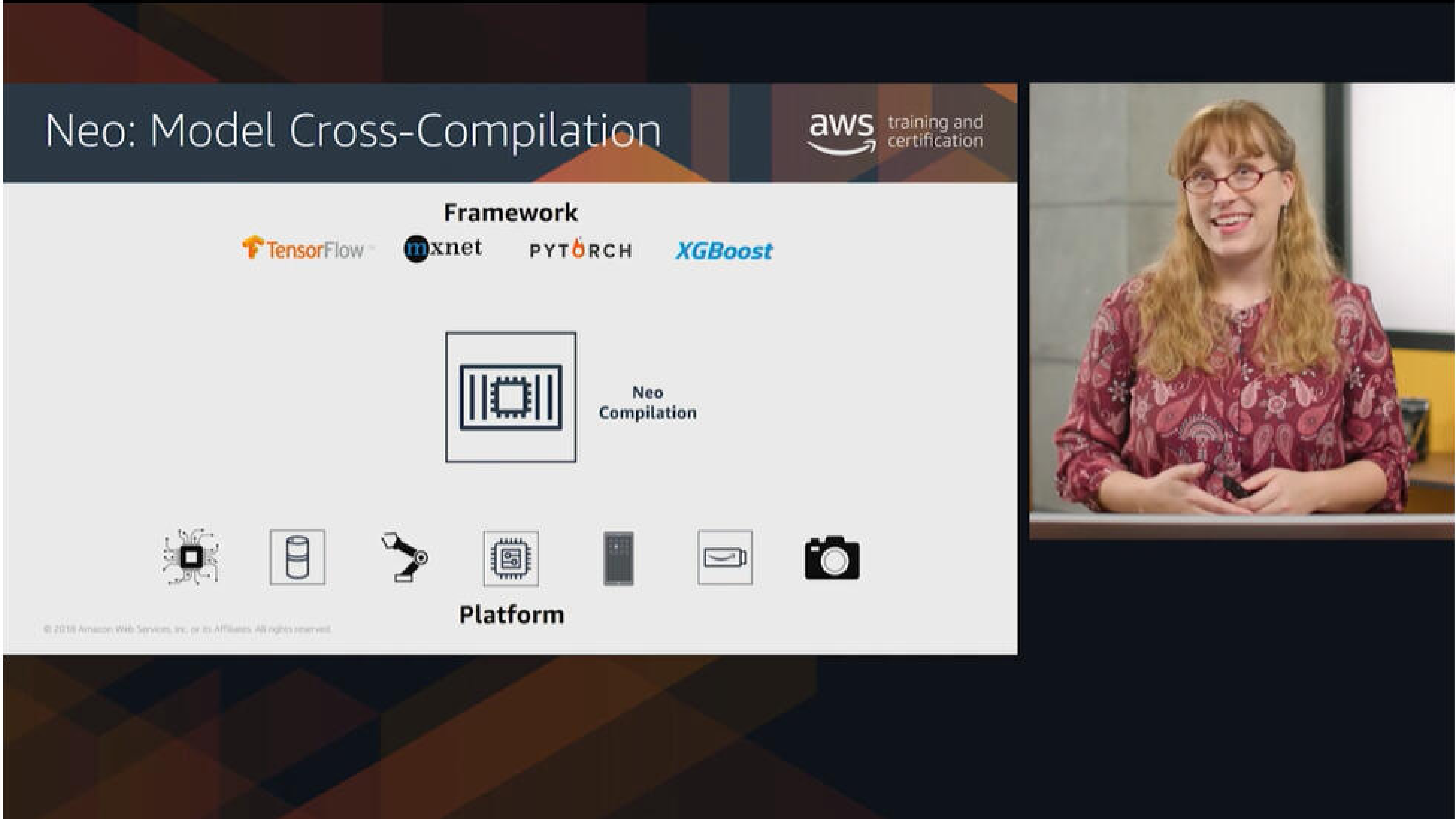
Neo: Model Cross-Compilation
aws training and certification
Framework
TensorFlow
mxnet
PYTORCH
XGBoost
Neo Compilation
Platform
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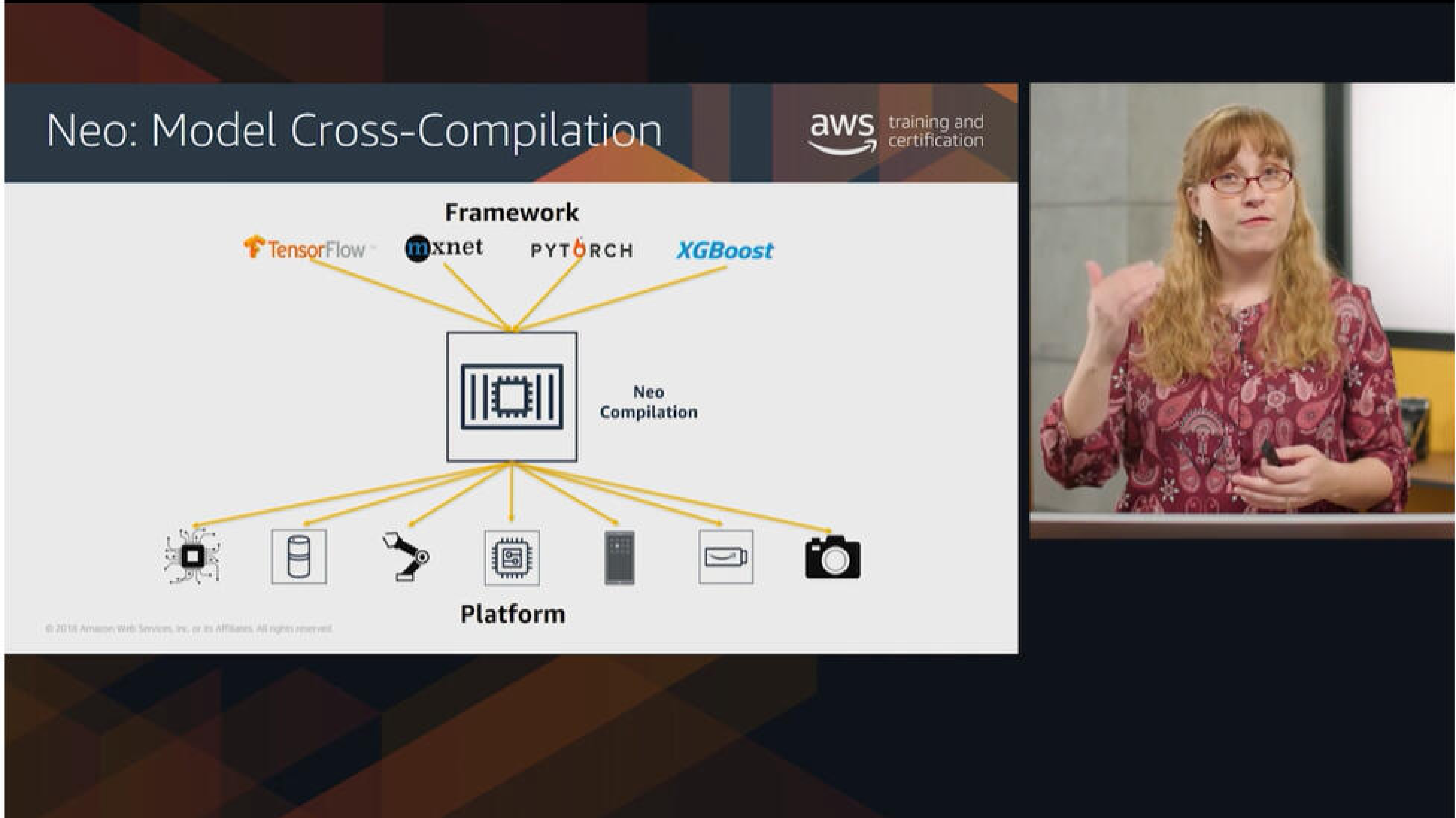
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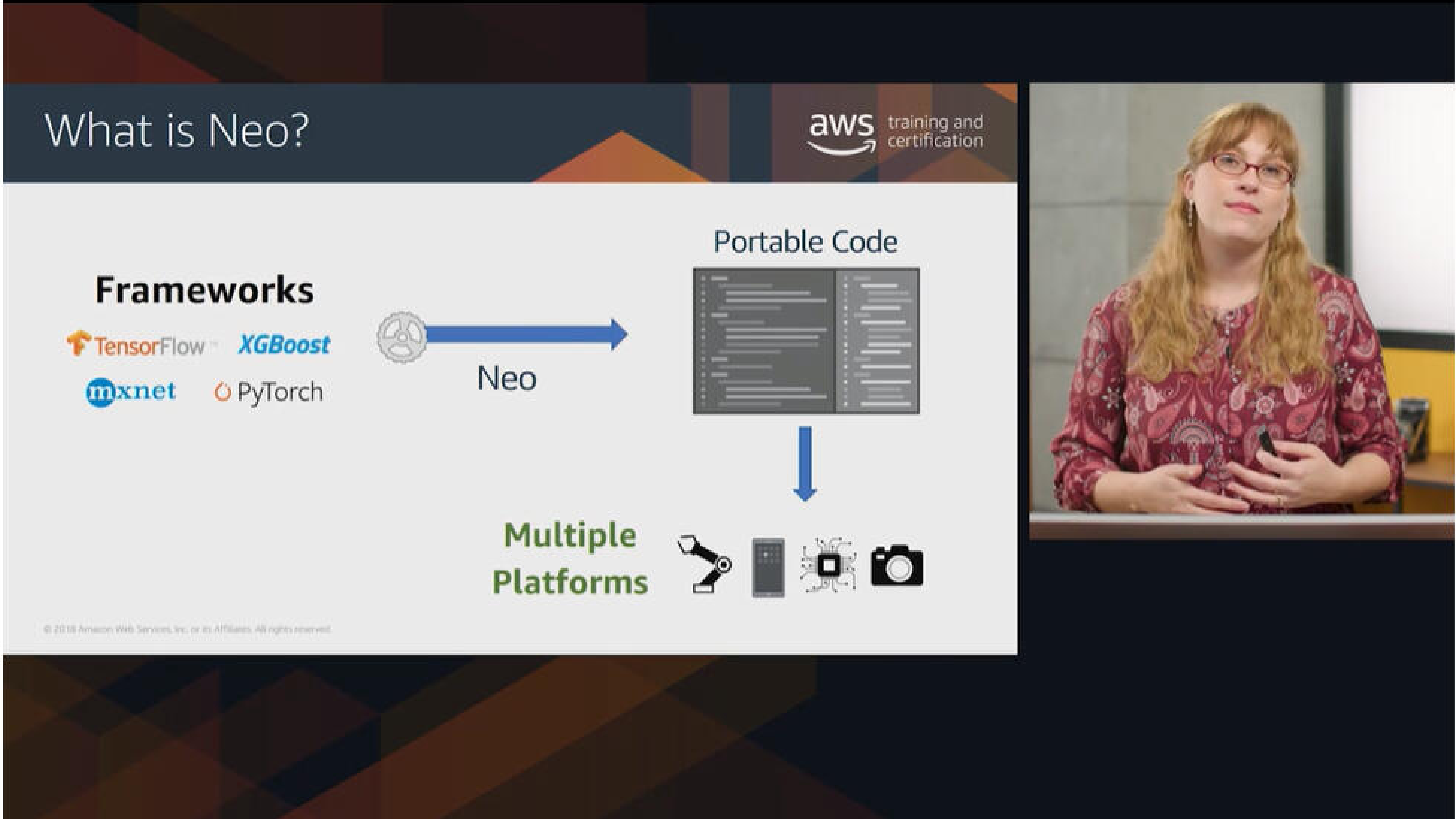
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Frameworks
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XGBoost
mxnet
PyTorch
Neo
Portable Code
Multiple Platforms
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Neo Components

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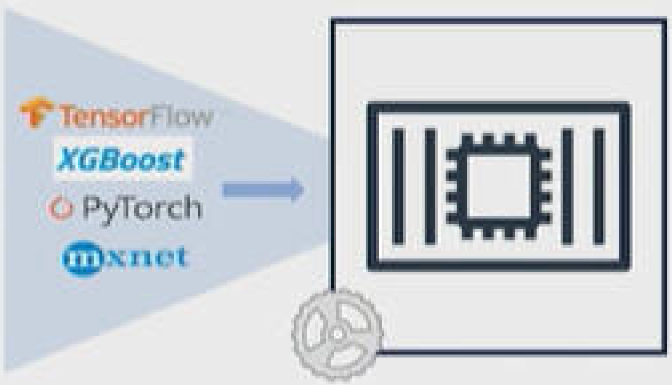
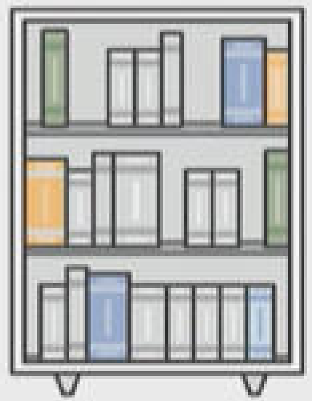
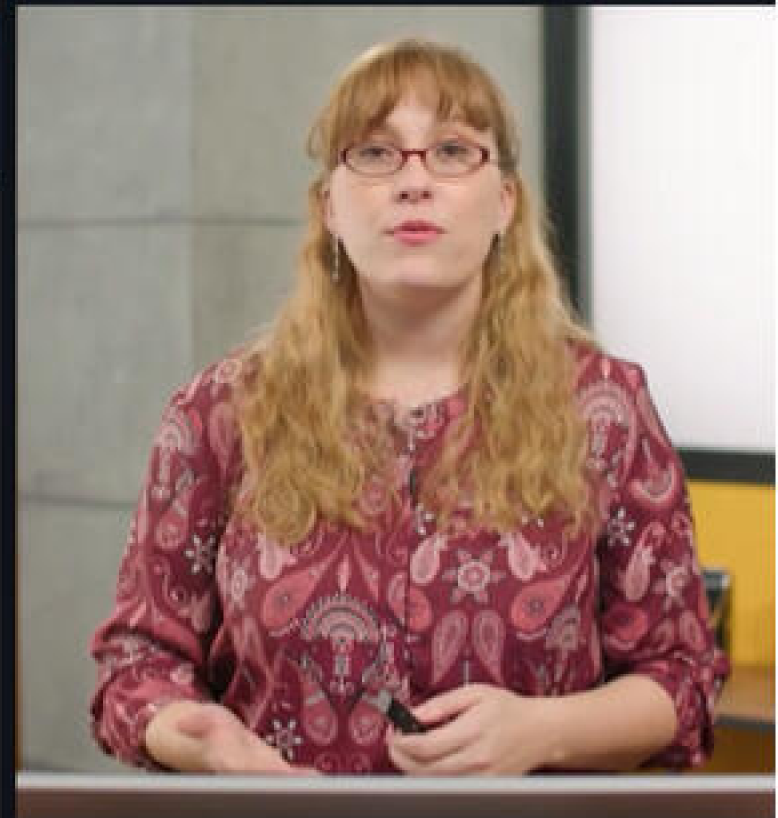


Neo Compiler Container



Shared Object Library



How Does Neo Work?

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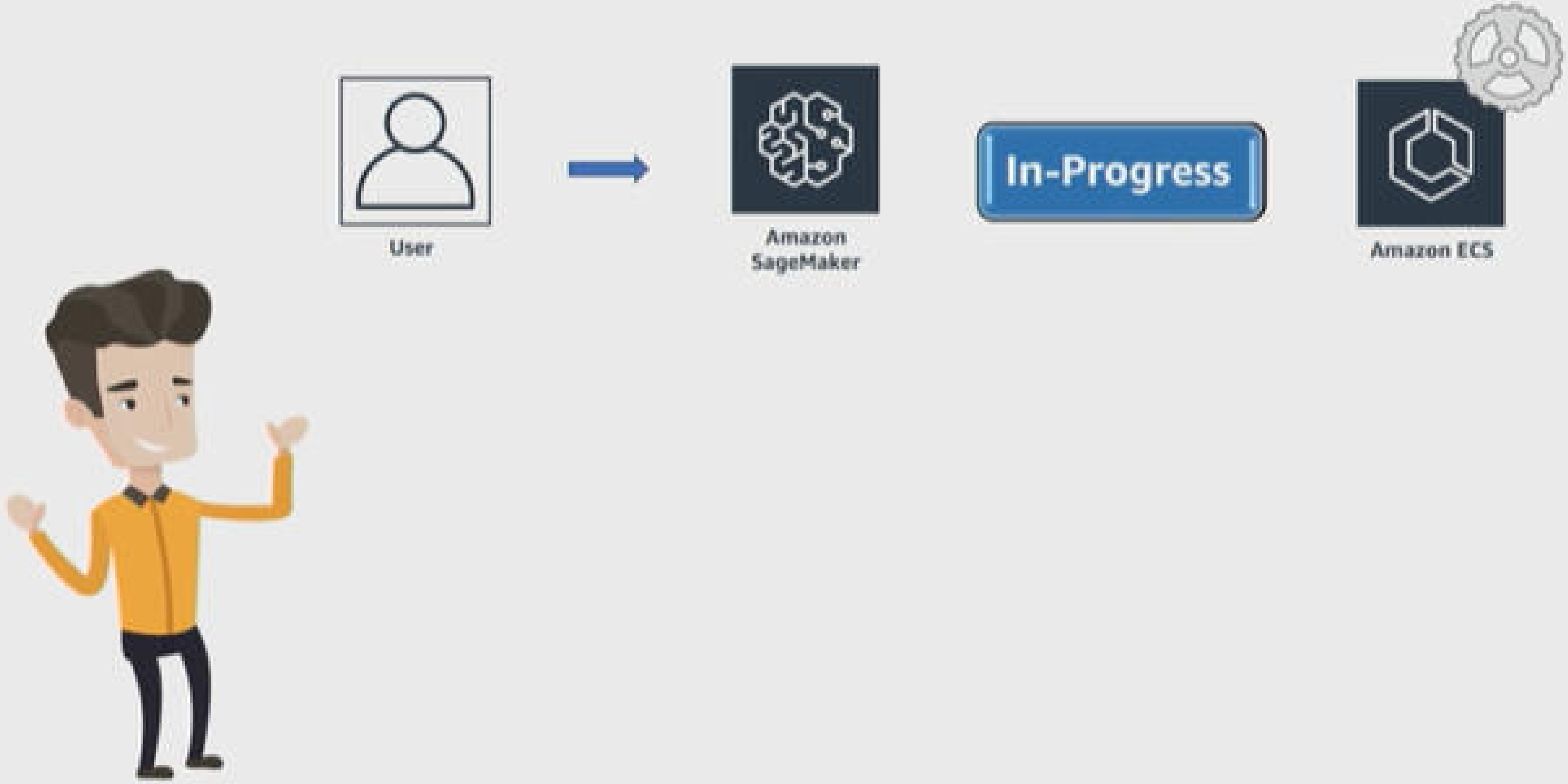

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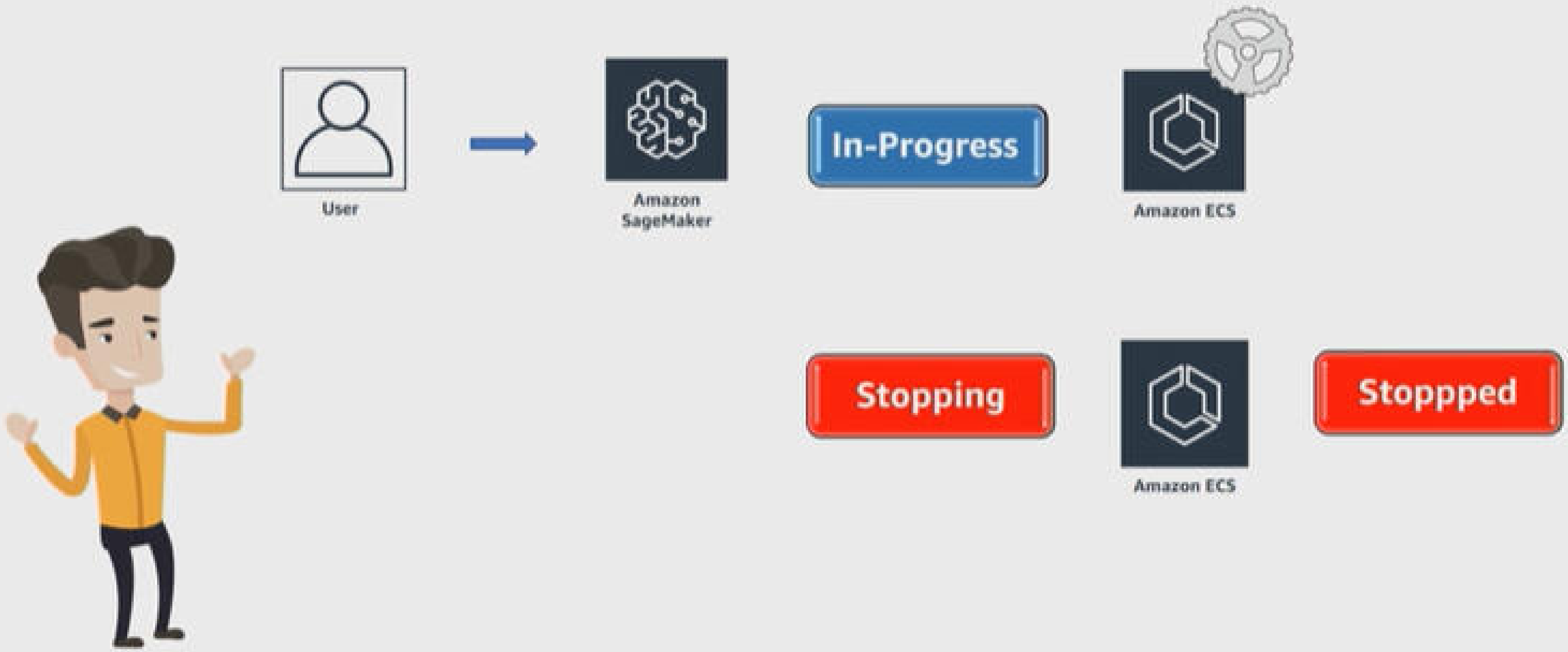

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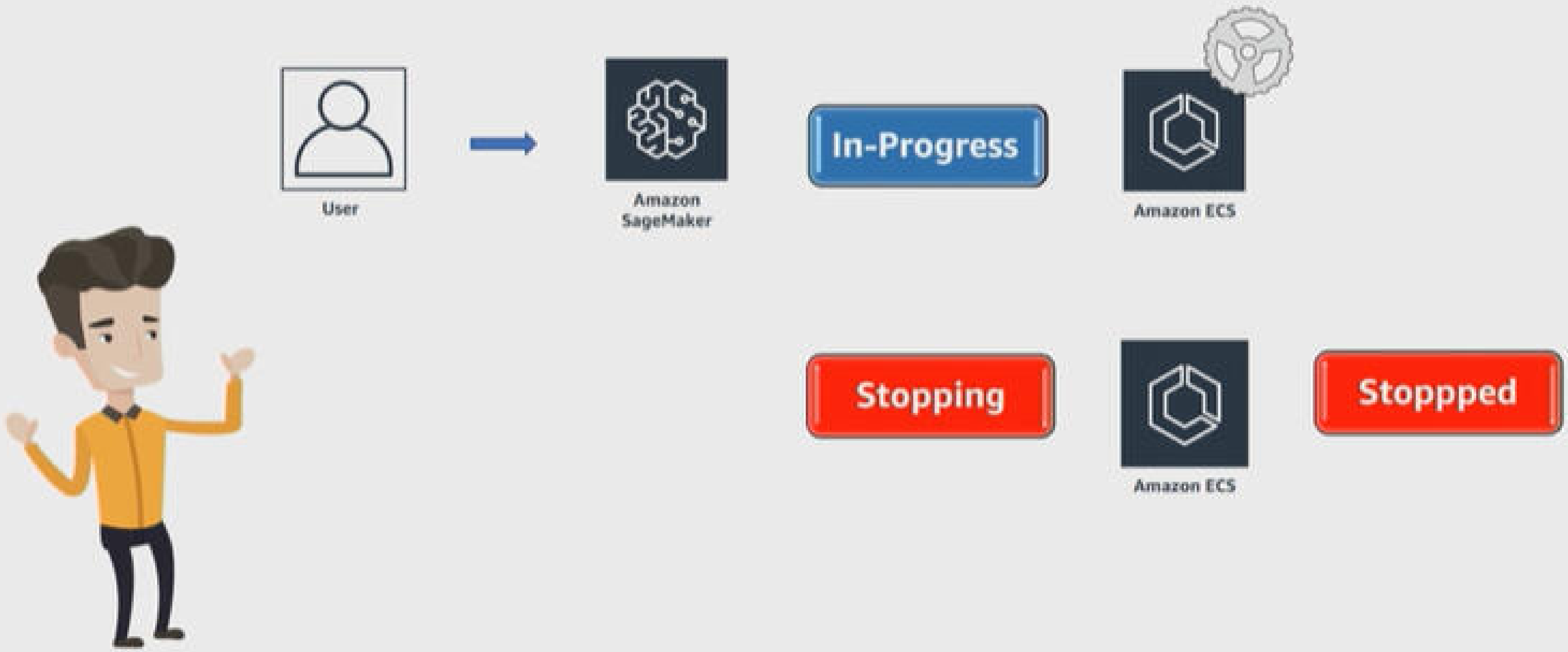

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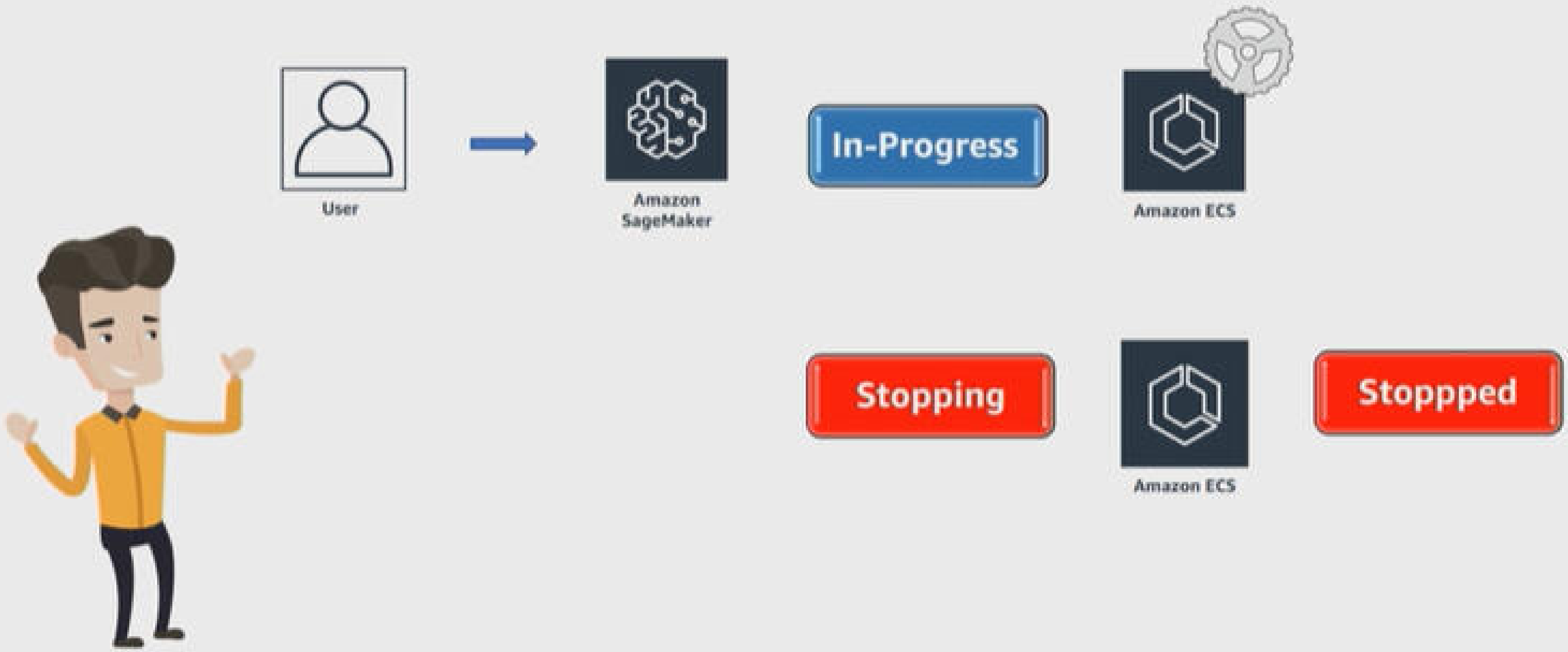

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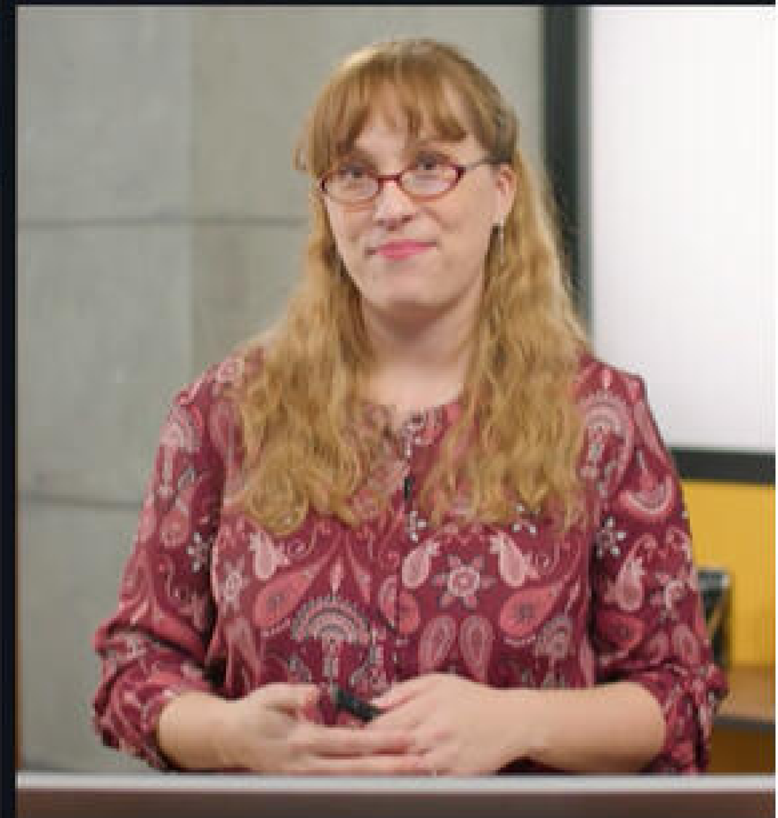

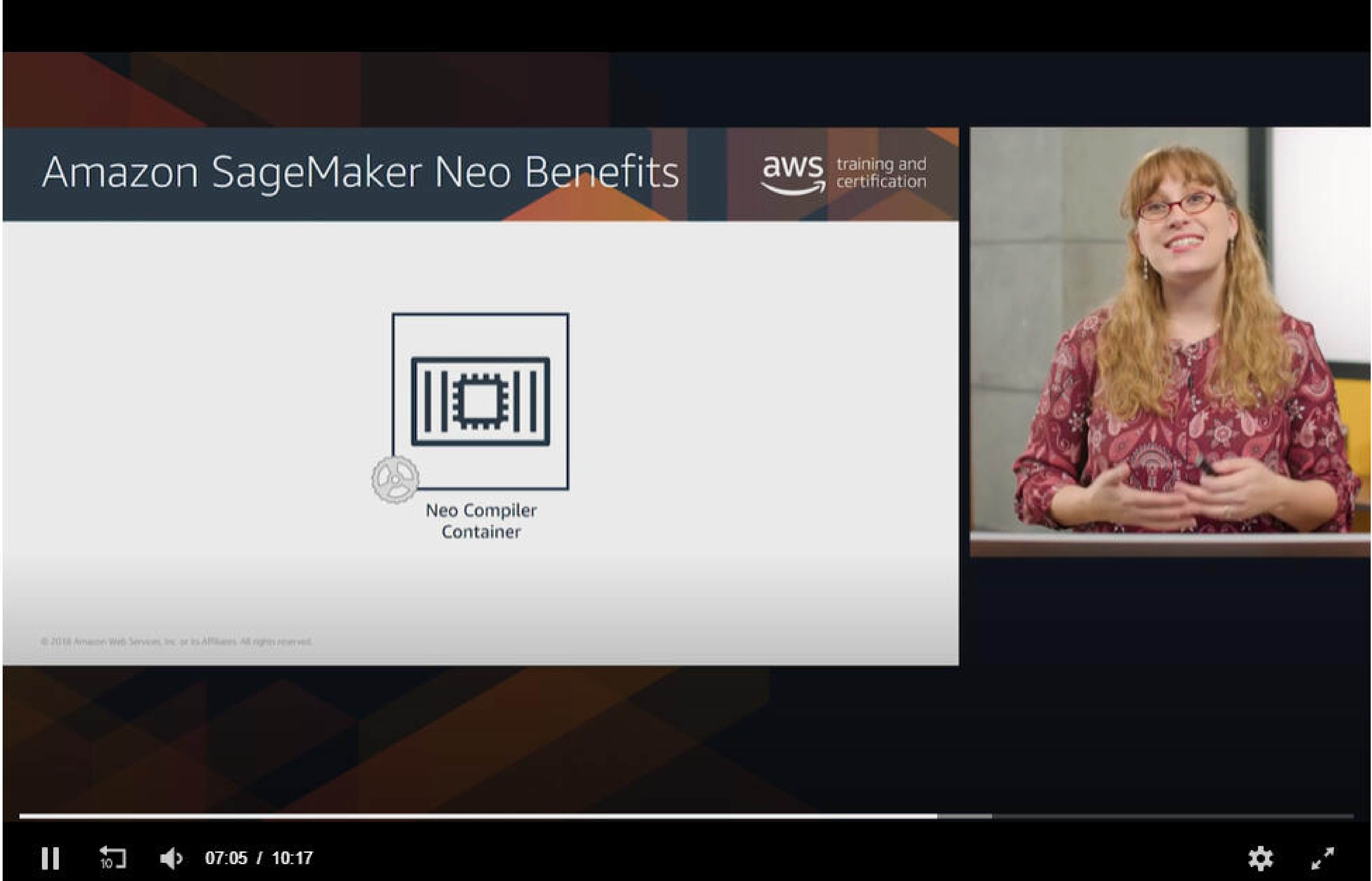
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Neo Compiler Container
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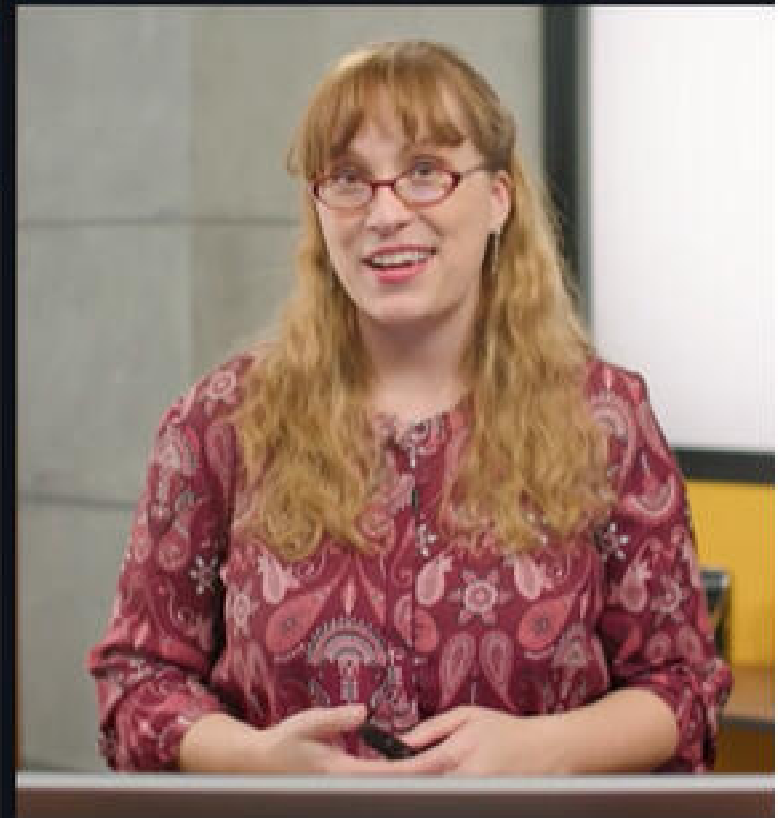
07:05 / 10:17

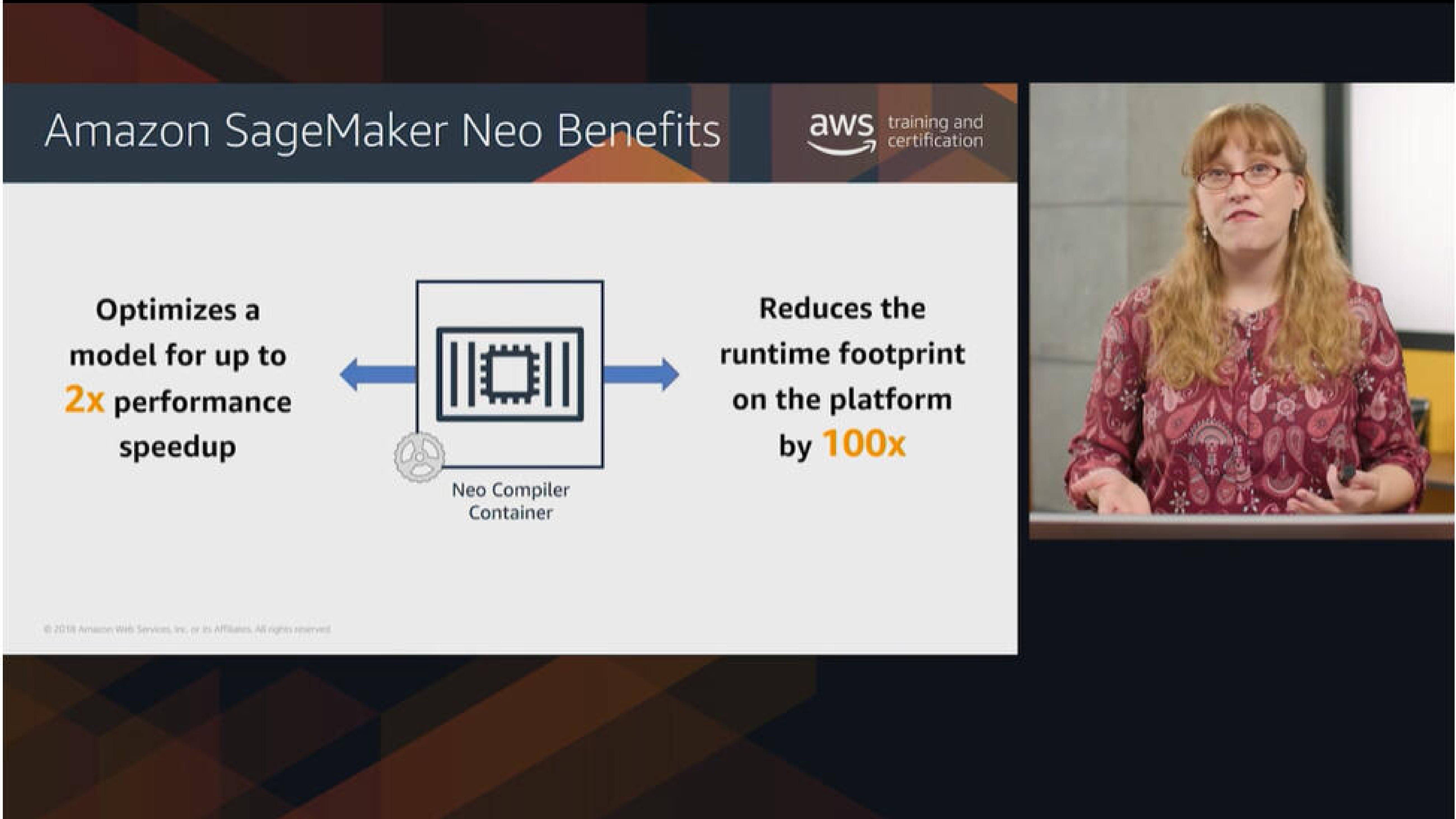
Amazon SageMaker Neo Benefits

aws training and certification

Optimizes a model for up to 2x performance speedup

Neo Compiler Container





Amazon SageMaker Neo Benefits
aws training and certification
Optimizes a model for up to 2x performance speedup
Neo Compiler Container
Reduces the runtime footprint on the platform by 100x
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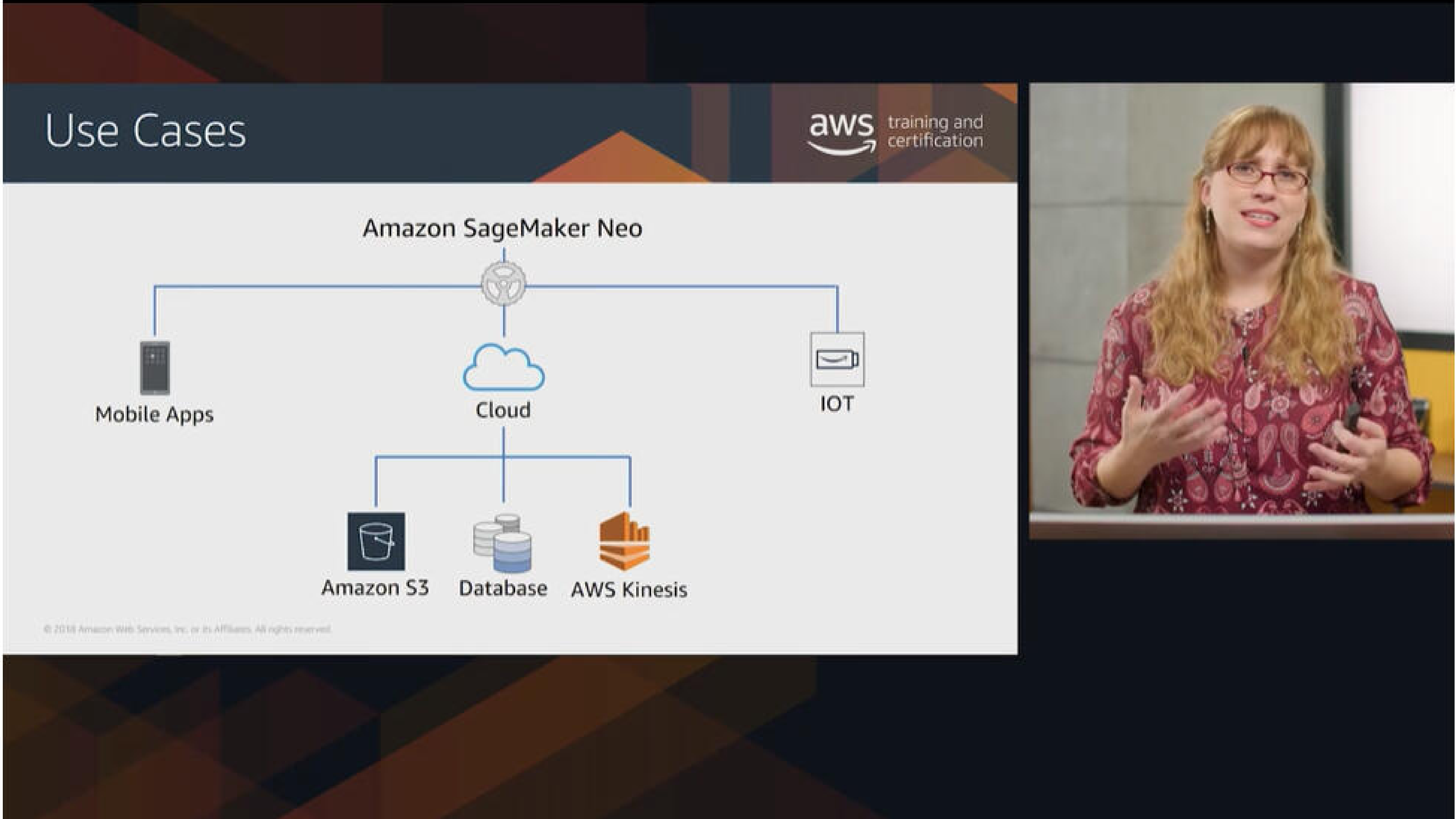
Use Cases
aws training and certification
Amazon SageMaker Neo
Mobile Apps
Cloud
IOT
Amazon S3
Database
AWS Kinesis

Key Takeaways

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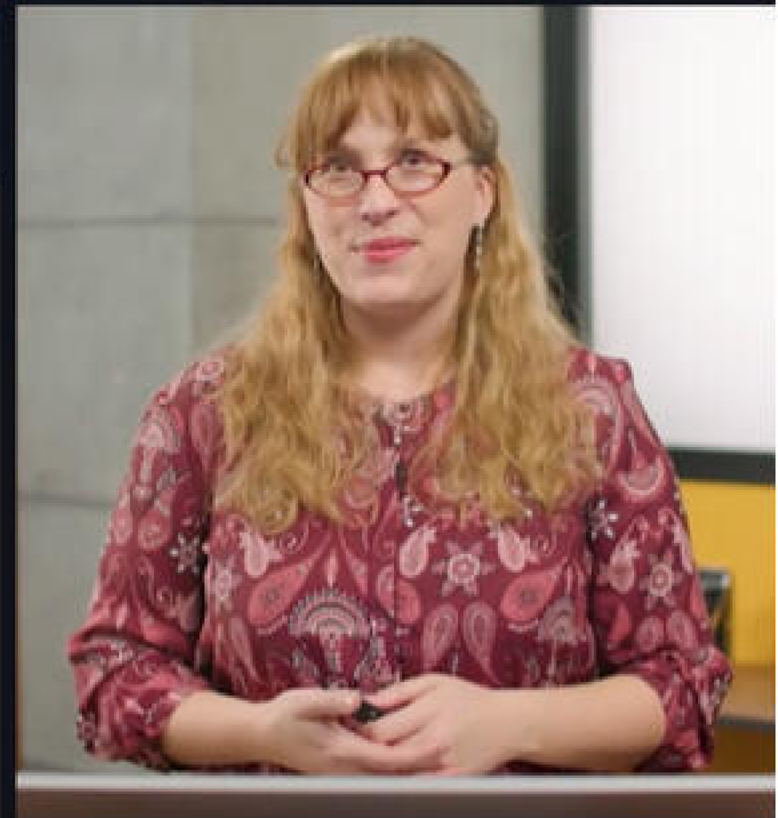
- Popular deep learning and decision tree models.
- Apache MXNet, TensorFlow, PyTorch, XGBoost.
- Various Amazon EC2 instances and edge devices.
- Up to 2x performance speedup and 100x memory footprint reduction at no additional charge.



What is Ground Truth?

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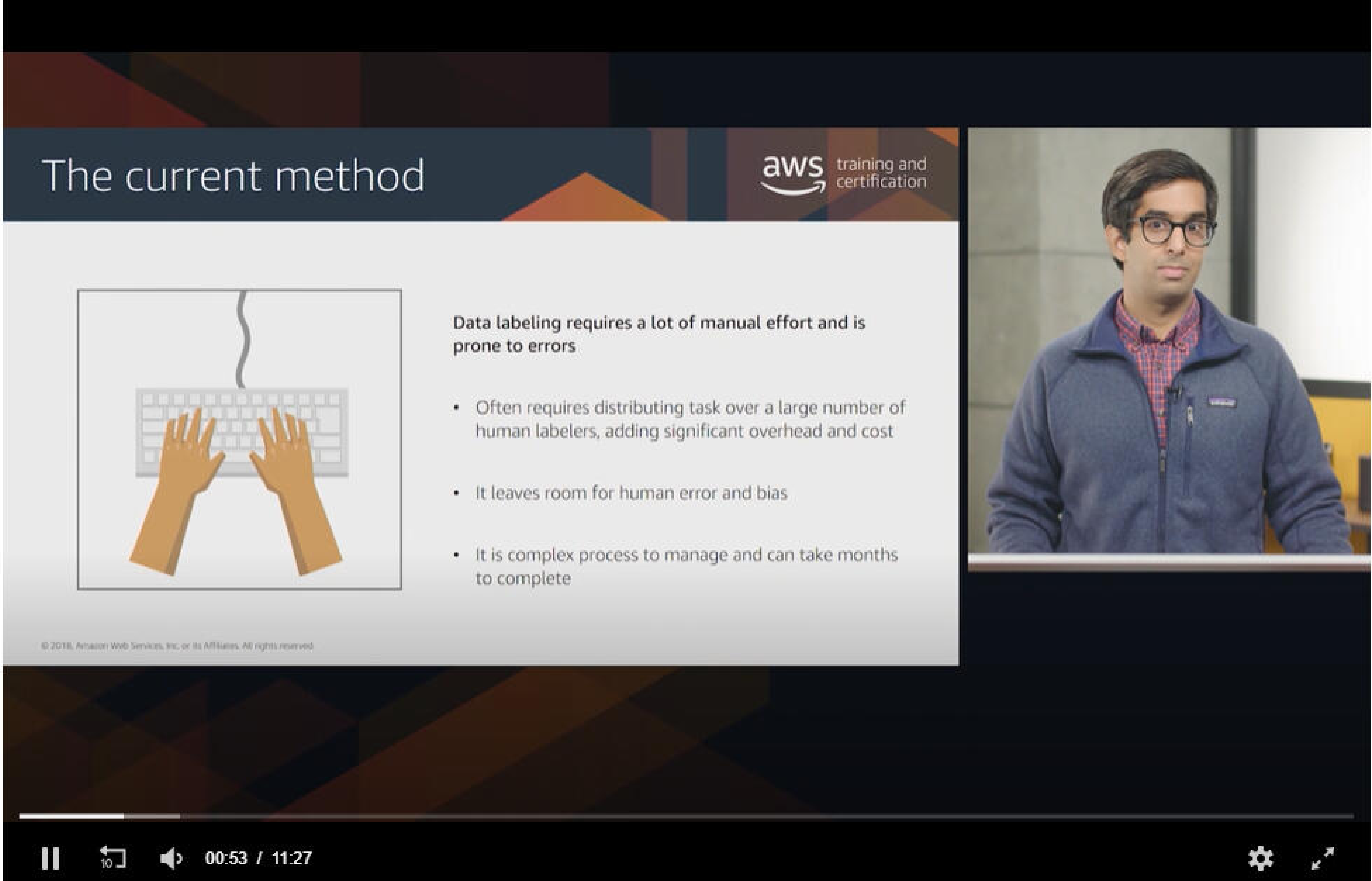
The current method
aws training and certification
Data labeling requires a lot of manual effort and is prone to errors
• Often requires distributing task over a large number of human labelers, adding significant overhead and cost
• It leaves room for human error and bias
• It is complex process to manage and can take months to complete
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00:53 / 11:27

Ground Truth fixes these pain points

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Amazon Simple Storage Service (S3)

Ground Truth Labeling Jobs

- Managed experience where customers can set up a labeling job in a just a few steps
- Templates for common labeling tasks
- Built-in features to improve labeling accuracy
- Selection from multiple labeling workforces

Human labeling

You have three options when selecting a workforce to perform your labeling

Public crowdsourced workforce

Pre-approved third-party vendors

Your own internal workforce

Better labeling accuracy

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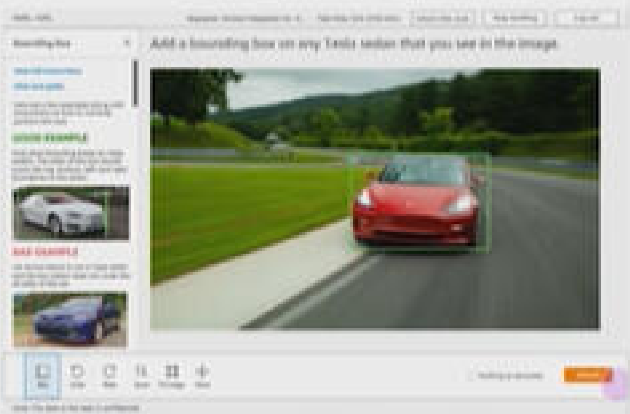
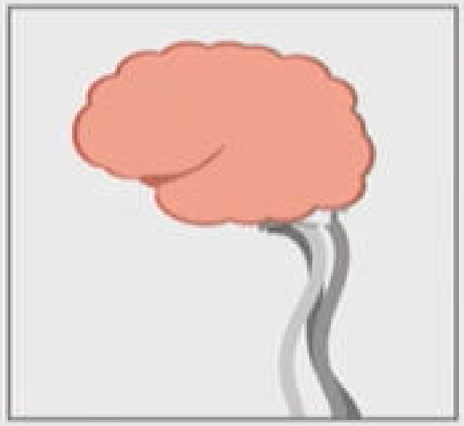
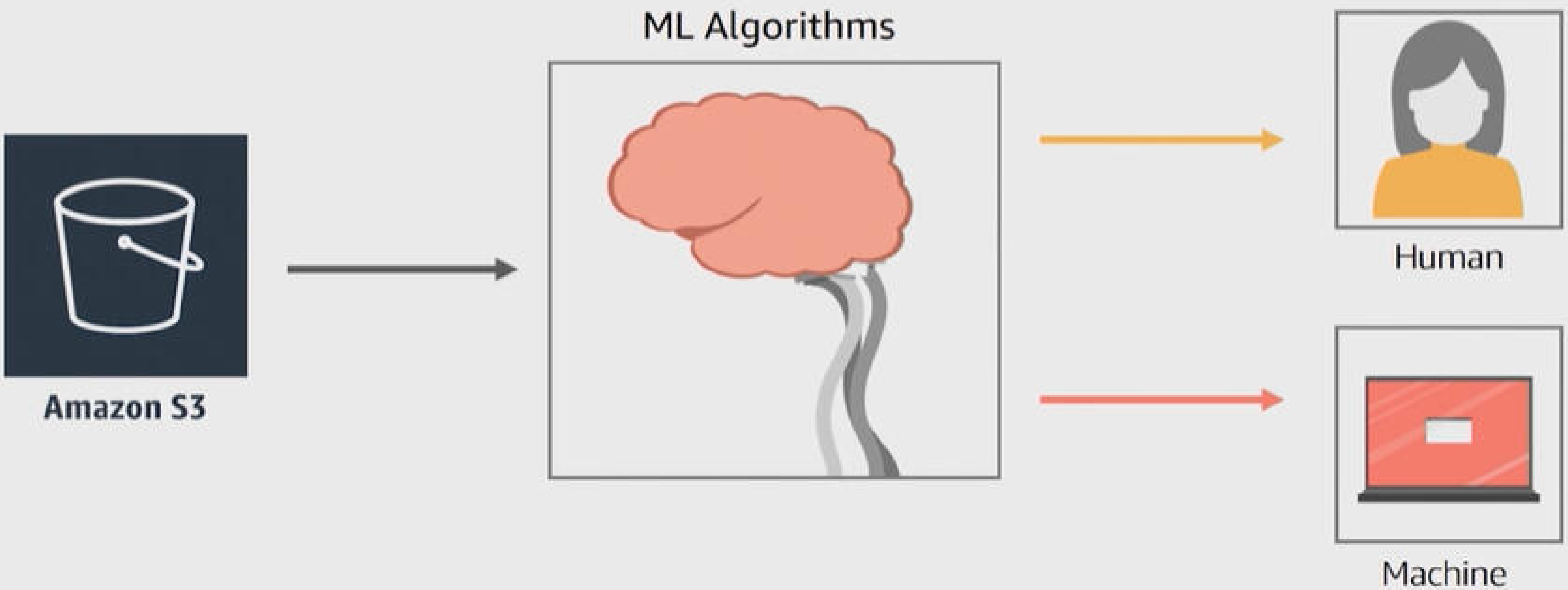
Innovative UX Techniques



Built-in Algorithms



Automatic labeling



How automatic labeling works

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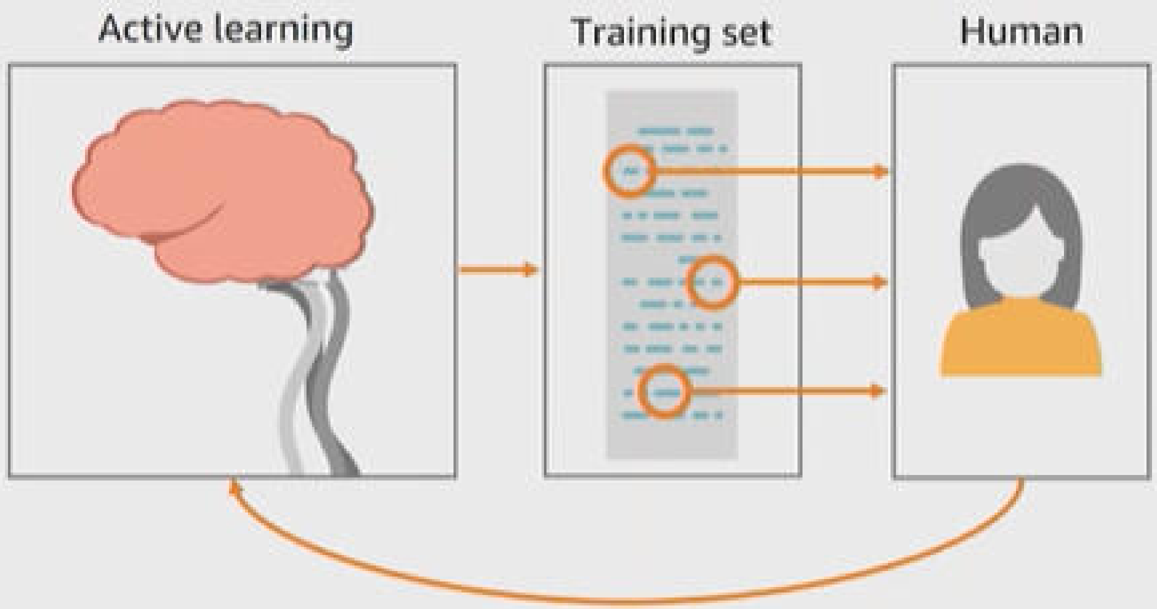

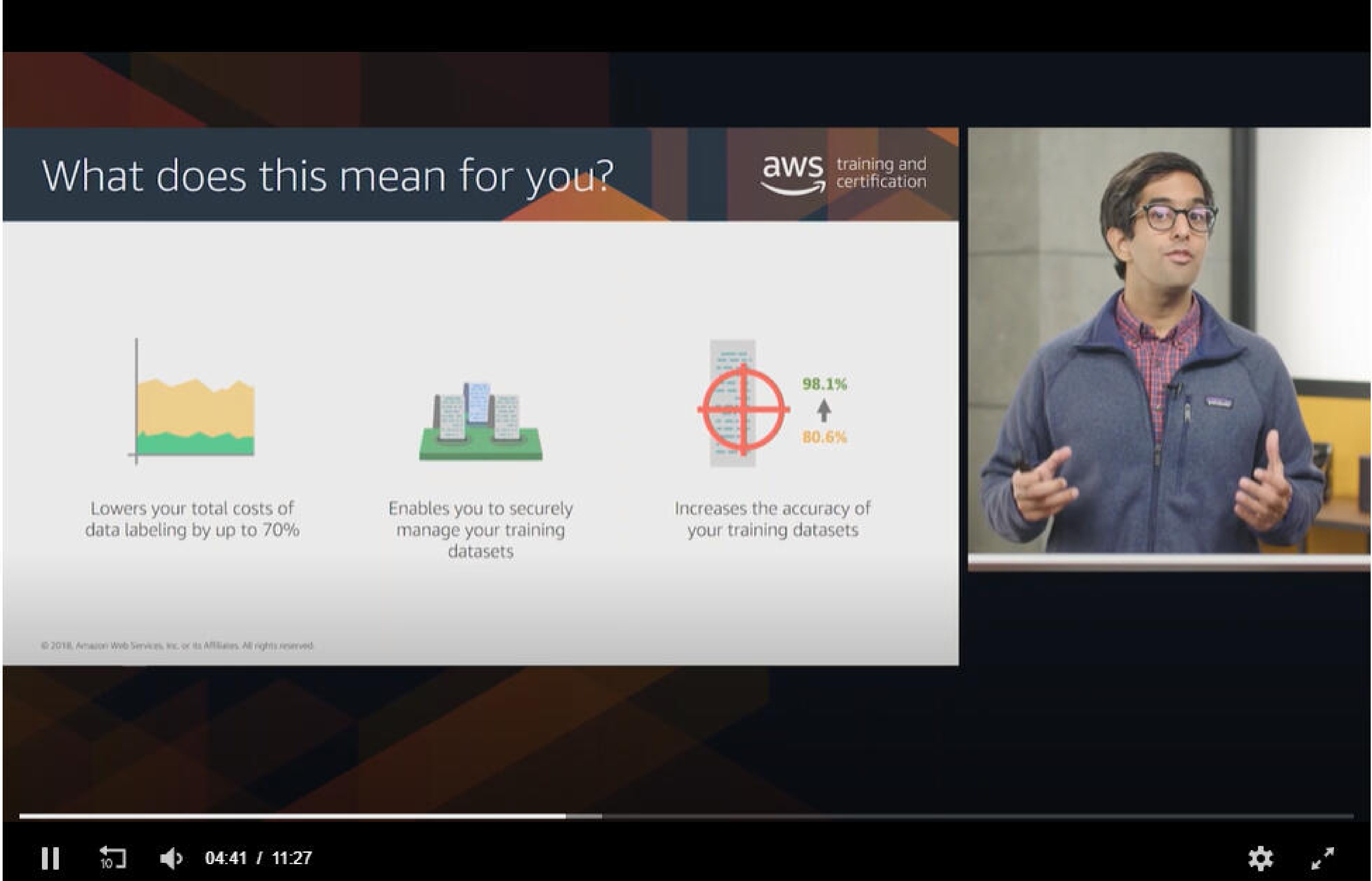
What does this mean for you?
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98.1%
80.6%
Lowers your total costs of data labeling by up to 70%
Enables you to securely manage your training datasets
Increases the accuracy of your training datasets
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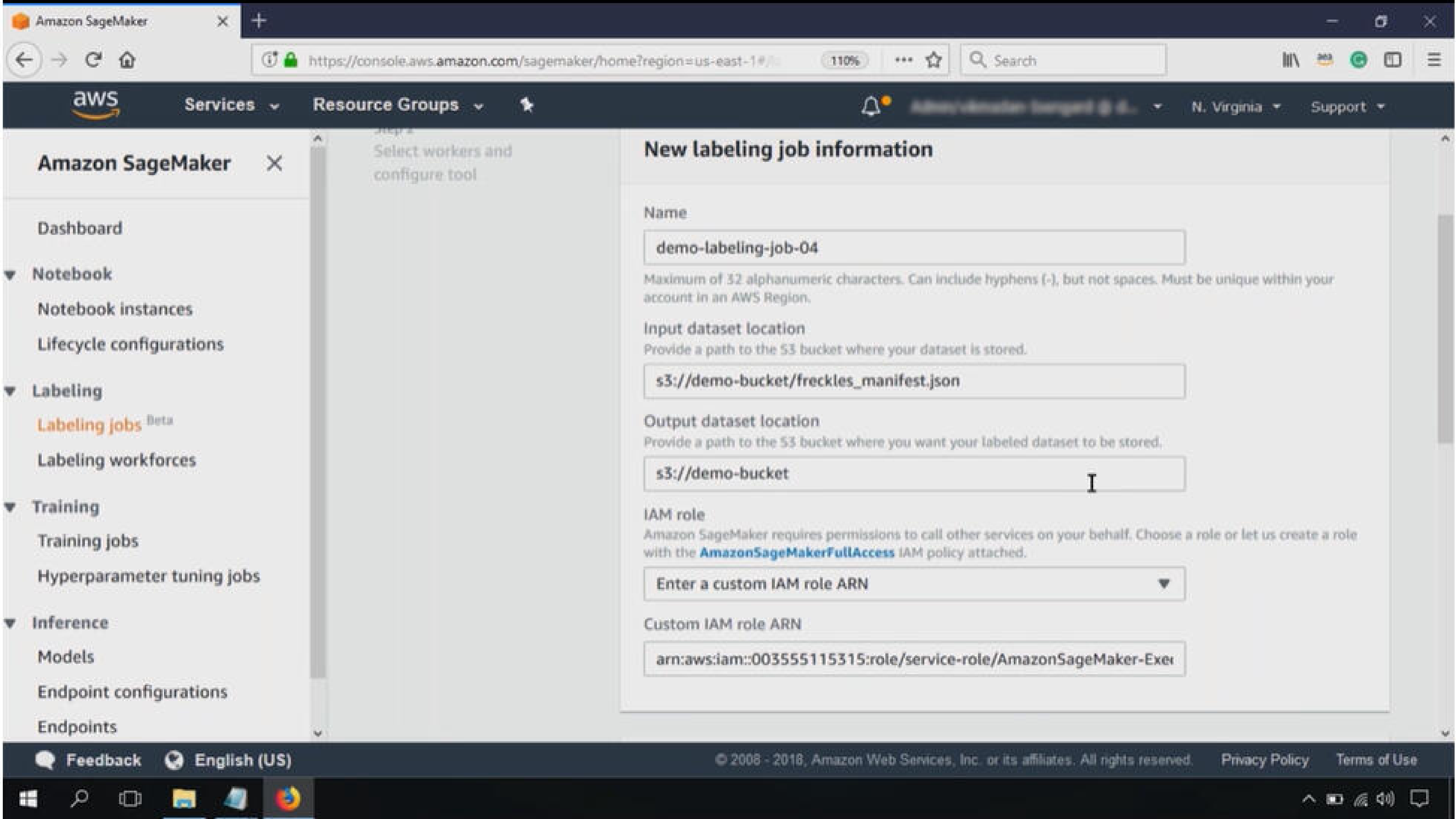
04:41 / 11:27


Amazon SageMaker
https://console.aws.amazon.com/sagemaker/home?region=us-east-1#/
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Search
Services
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Support
Select workers and configure tool
New labeling job information
Name
demo-labeling-job-04
Maximum of 32 alphanumeric characters. Can include hyphens (-), but not spaces. Must be unique within your account in an AWS Region.
Input dataset location
Provide a path to the S3 bucket where your dataset is stored.
s3://demo-bucket/freckles_manifest.json
Output dataset location
Provide a path to the S3 bucket where you want your labeled dataset to be stored.
s3://demo-bucket
IAM role
Amazon SageMaker requires permissions to call other services on your behalf. Choose a role or let us create a role with the AmazonSageMakerFullAccess IAM policy attached.
Enter a custom IAM role ARN
Custom IAM role ARN
arn:aws:iam::003555115315:role/service-role/AmazonSageMaker-Exe
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Feedback
English (US)
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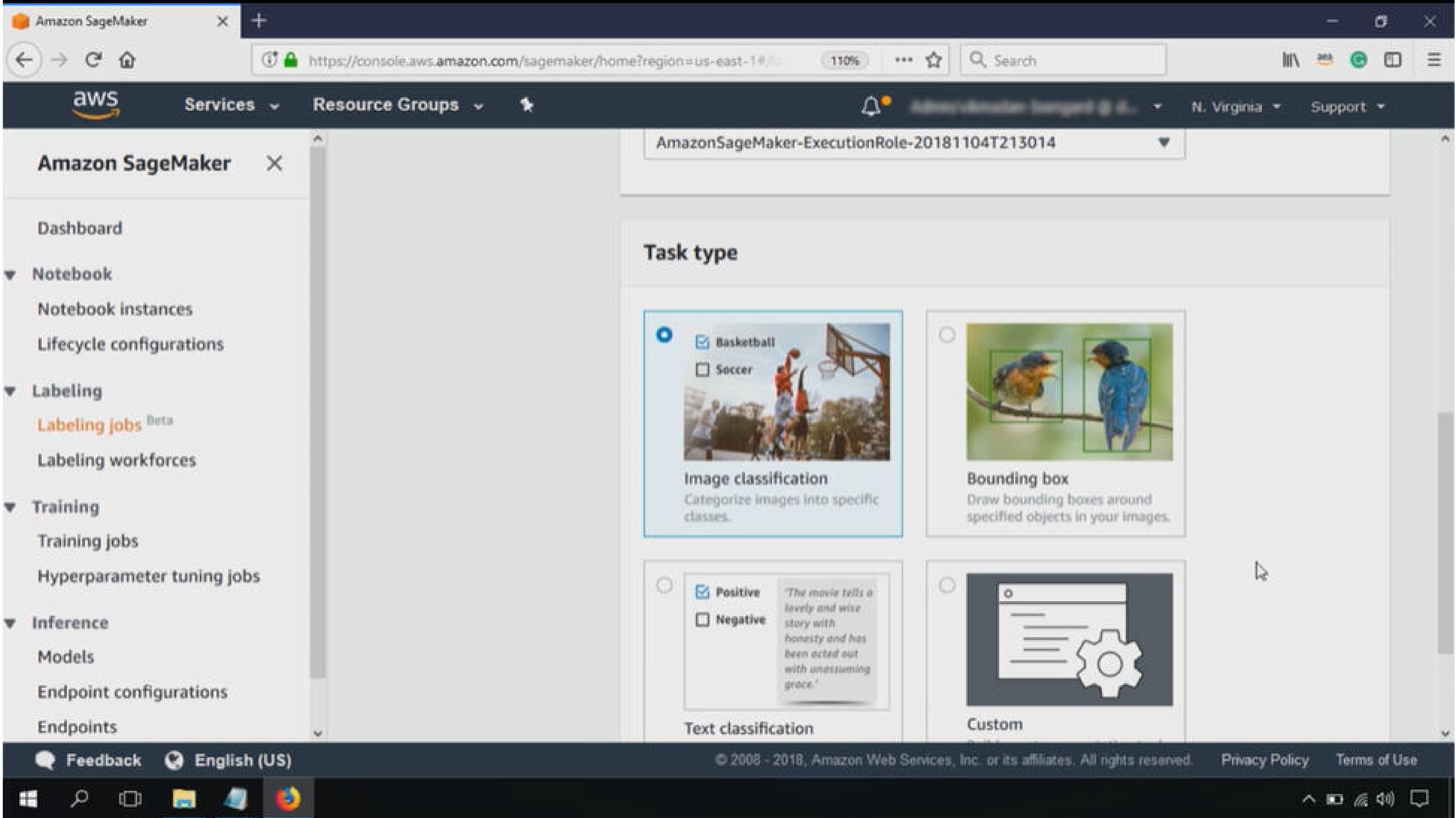

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AmazonSageMaker-ExecutionRole-20181104T213014
Task type
Basketball
Soccer
Image classification
Categorize images into specific classes.
Bounding box
Draw bounding boxes around specified objects in your images.
Positive
Negative
"The movie tells a lovely and wise story with honesty and has been acted out with unassuming grace."
Text classification
Custom
Feedback
English (US)
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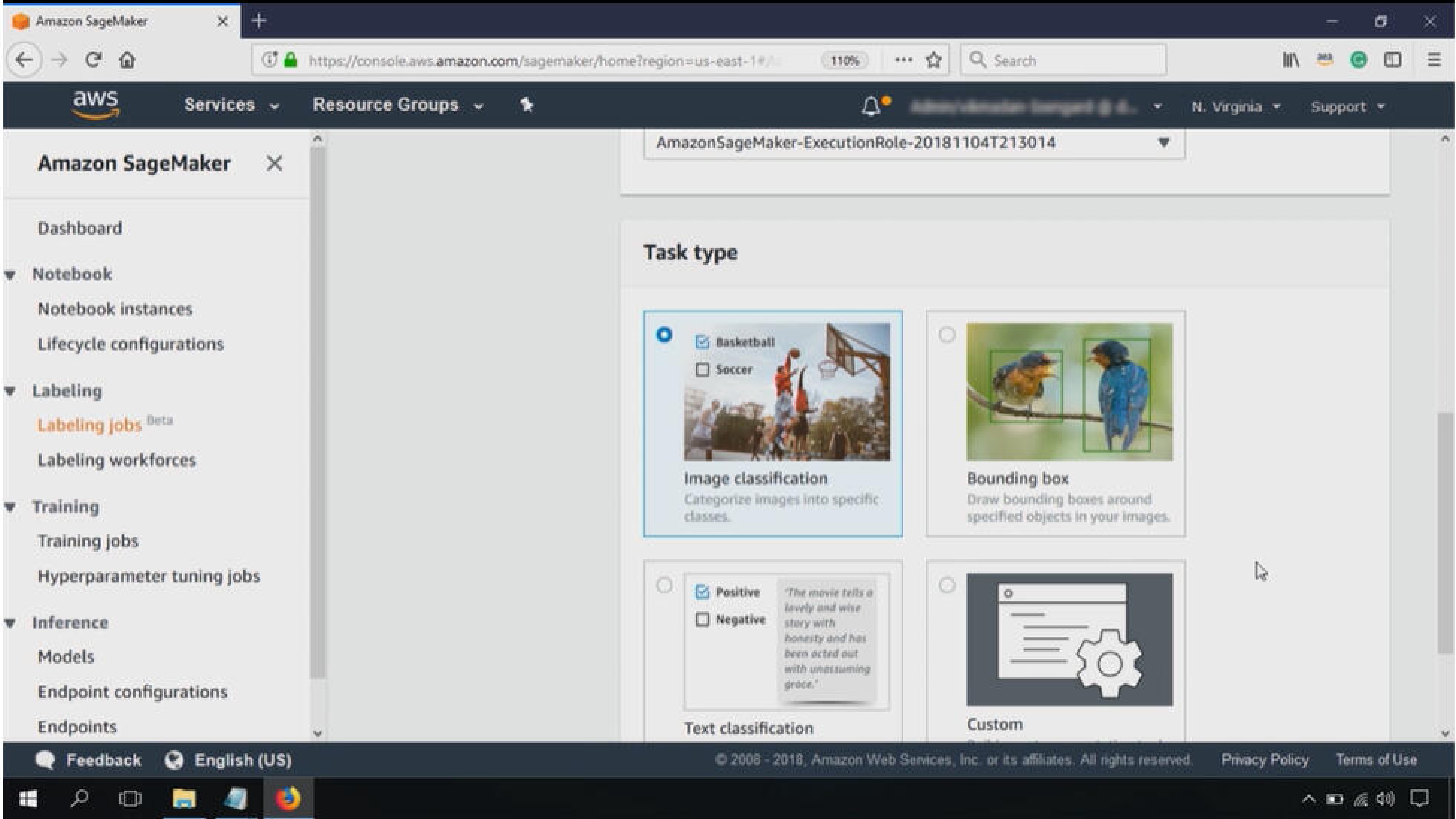
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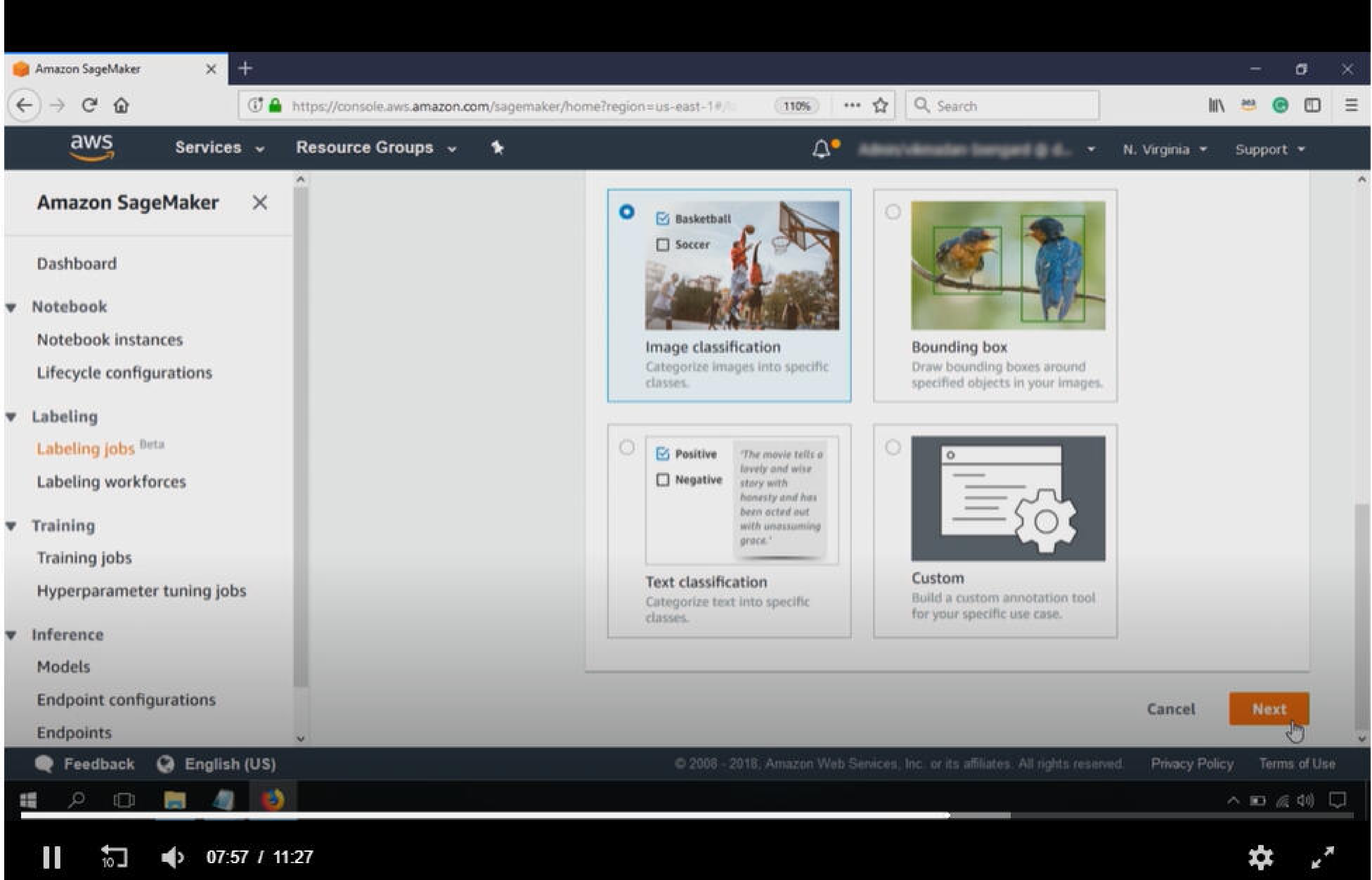

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Image classification
Categorize images into specific classes.
Bounding box
Draw bounding boxes around specified objects in your images.
Positive
Negative
"The movie tells a lovely and wise story with honesty and has been acted out with unassuming grace."
Text classification
Categorize text into specific classes.
Custom
Build a custom annotation tool for your specific use case.
Cancel
Next
Feedback
English (US)
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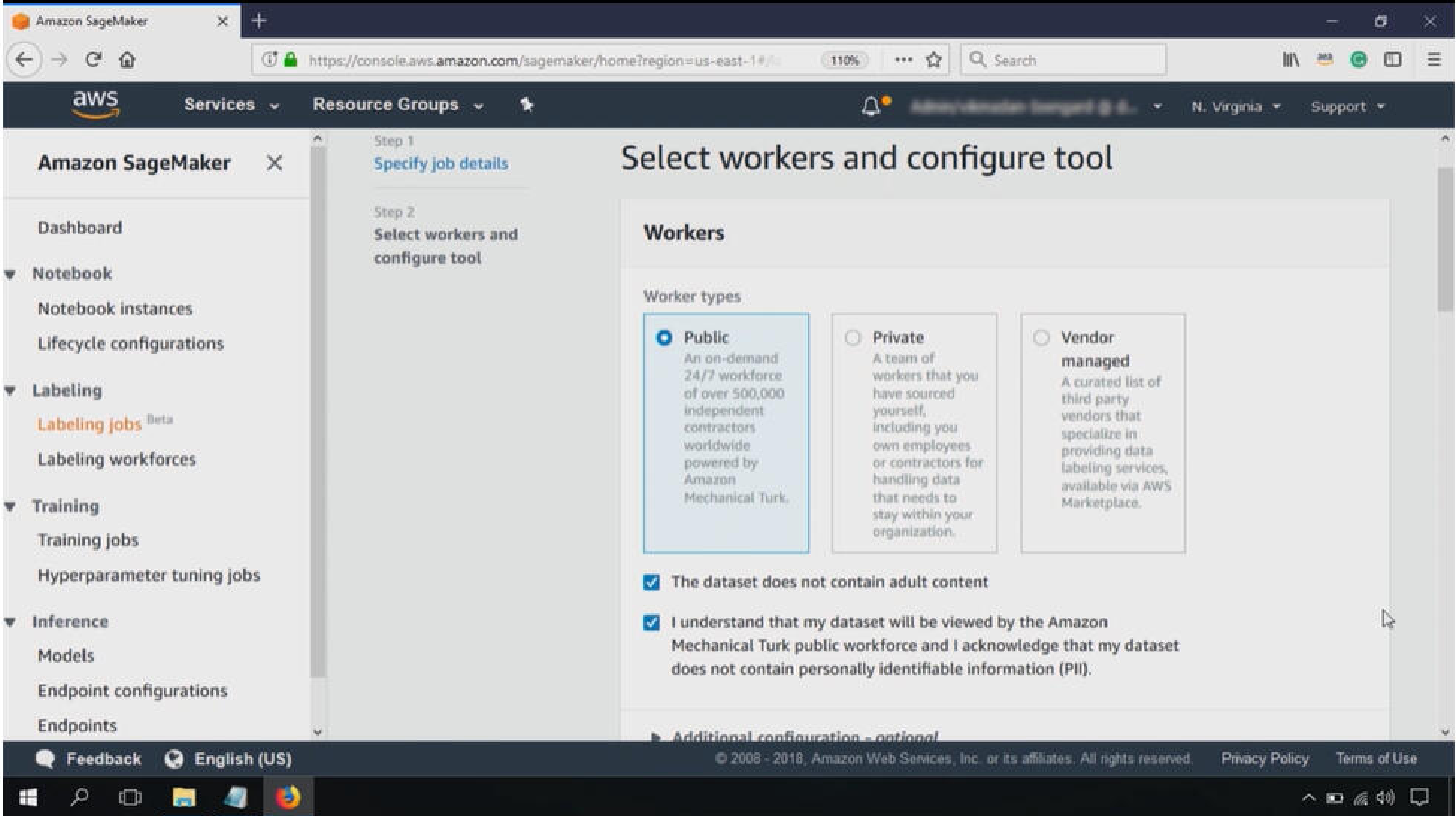
07:57 / 11:27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Step 1
Specify job details
Step 2
Select workers and configure tool
Select workers and configure tool
Workers
Worker types
Public
An on-demand 24/7 workforce of over 500,000 independent contractors worldwide powered by Amazon Mechanical Turk.
Private
A team of workers that you have sourced yourself, including you own employees or contractors for handling data that needs to stay within your organization.
Vendor managed
A curated list of third party vendors that specialize in providing data labeling services, available via AWS Marketplace.
The dataset does not contain adult content
I understand that my dataset will be viewed by the Amazon Mechanical Turk public workforce and I acknowledge that my dataset does not contain personally identifiable information (PII).
Additional configuration - optional
Feedback
English (US)
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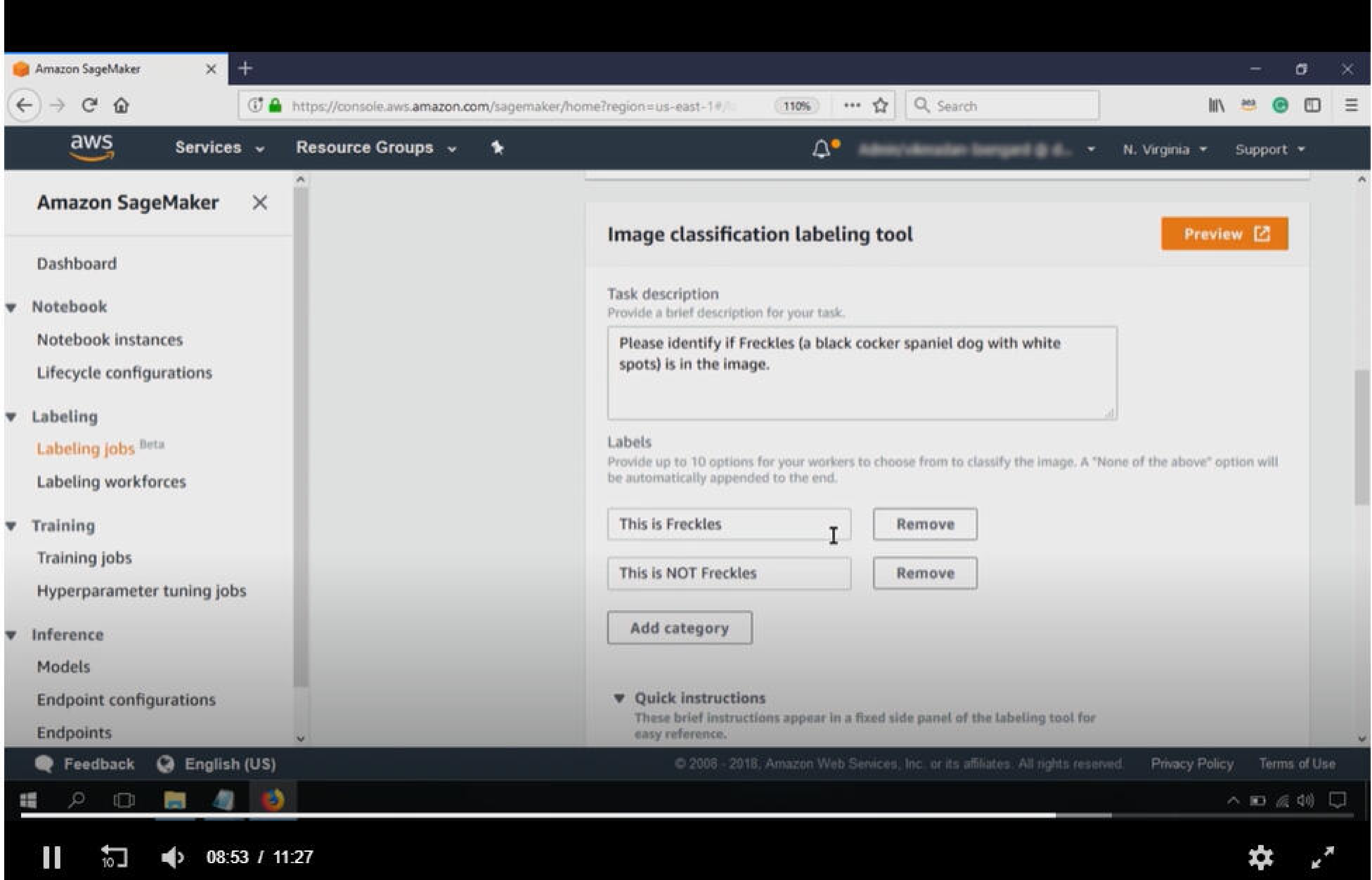
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Image classification labeling tool
Preview
Task description
Provide a brief description for your task.
Please identify if Freckles (a black cocker spaniel dog with white spots) is in the image.
Labels
Provide up to 10 options for your workers to choose from to classify the image. A "None of the above" option will be automatically appended to the end.
This is Freckles
Remove
This is NOT Freckles
Remove
Add category
Quick instructions
These brief instructions appear in a fixed side panel of the labeling tool for easy reference.
Feedback
English (US)
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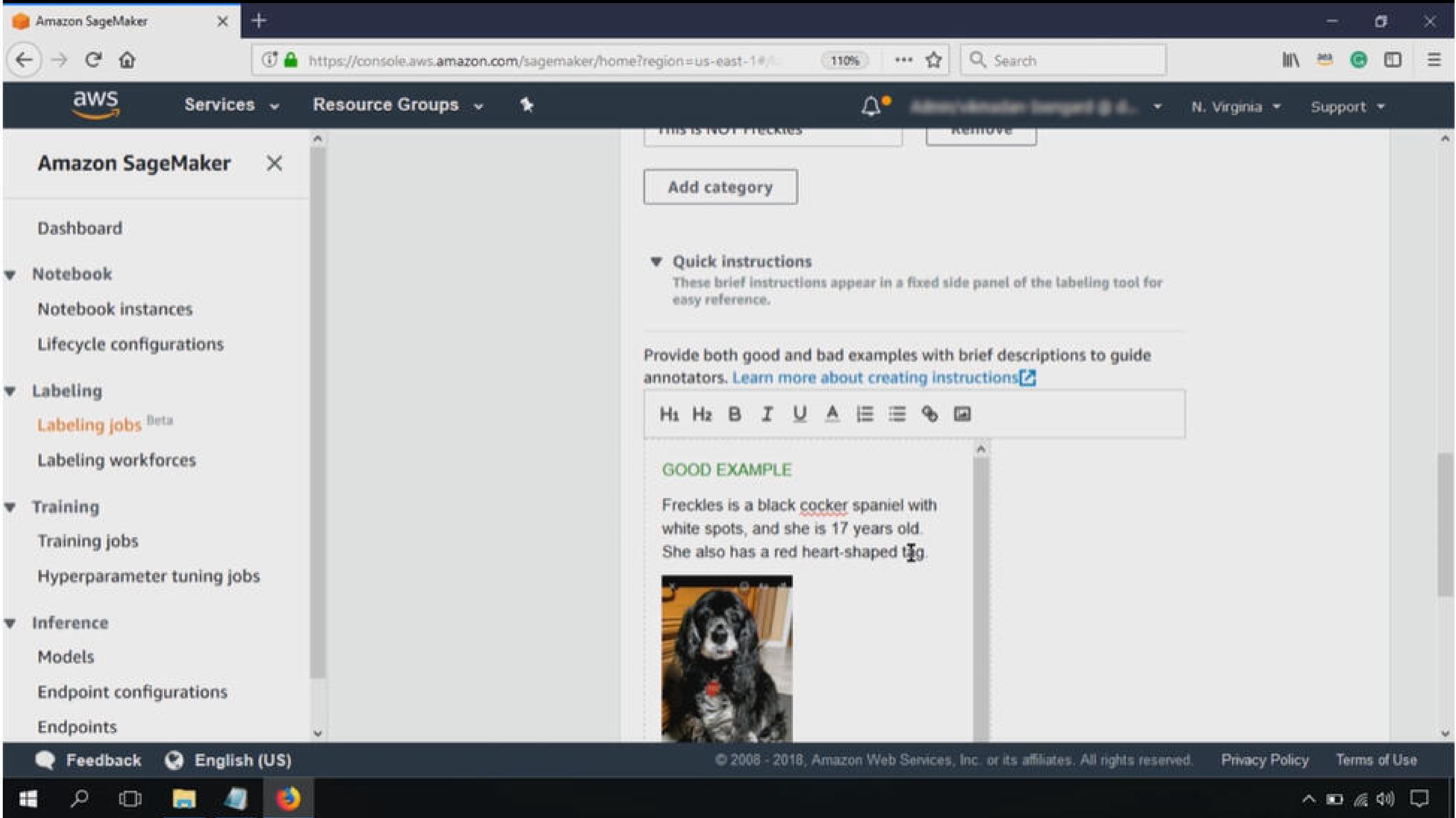
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Add category
Quick instructions
These brief instructions appear in a fixed side panel of the labeling tool for easy reference.
Provide both good and bad examples with brief descriptions to guide annotators. Learn more about creating instructions
H1 H2 B I U
GOOD EXAMPLE
Freckles is a black cocker spaniel with white spots, and she is 17 years old. She also has a red heart-shaped tag.
Feedback
English (US)
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  - Endpoints

Quick instructions

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Provide both good and bad examples with brief descriptions to guide annotators. Learn more about creating instructions

H1 H2 B I U A

GOOD EXAMPLE

Freckles is a black cocker spaniel with white spots, and she is 17 years old. She also has a red heart-shaped tag.

BAD EXAMPLE

Please make sure to mark dogs that are

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Quick instructions

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Provide both good and bad examples with brief descriptions to guide annotators. Learn more about creating instructions

GOOD EXAMPLE

Freckles is a black cocker spaniel with white spots, and she is 17 years old. She also has a red heart-shaped tag.

BAD EXAMPLE

Feedback | English (US)

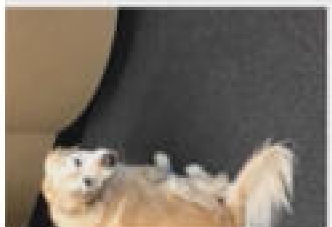
1. **Read** the task carefully and inspect the image.
2. **Read** the options and review the examples provided to understand more about the labels.
3. **Choose the** appropriate label that best suits the image.

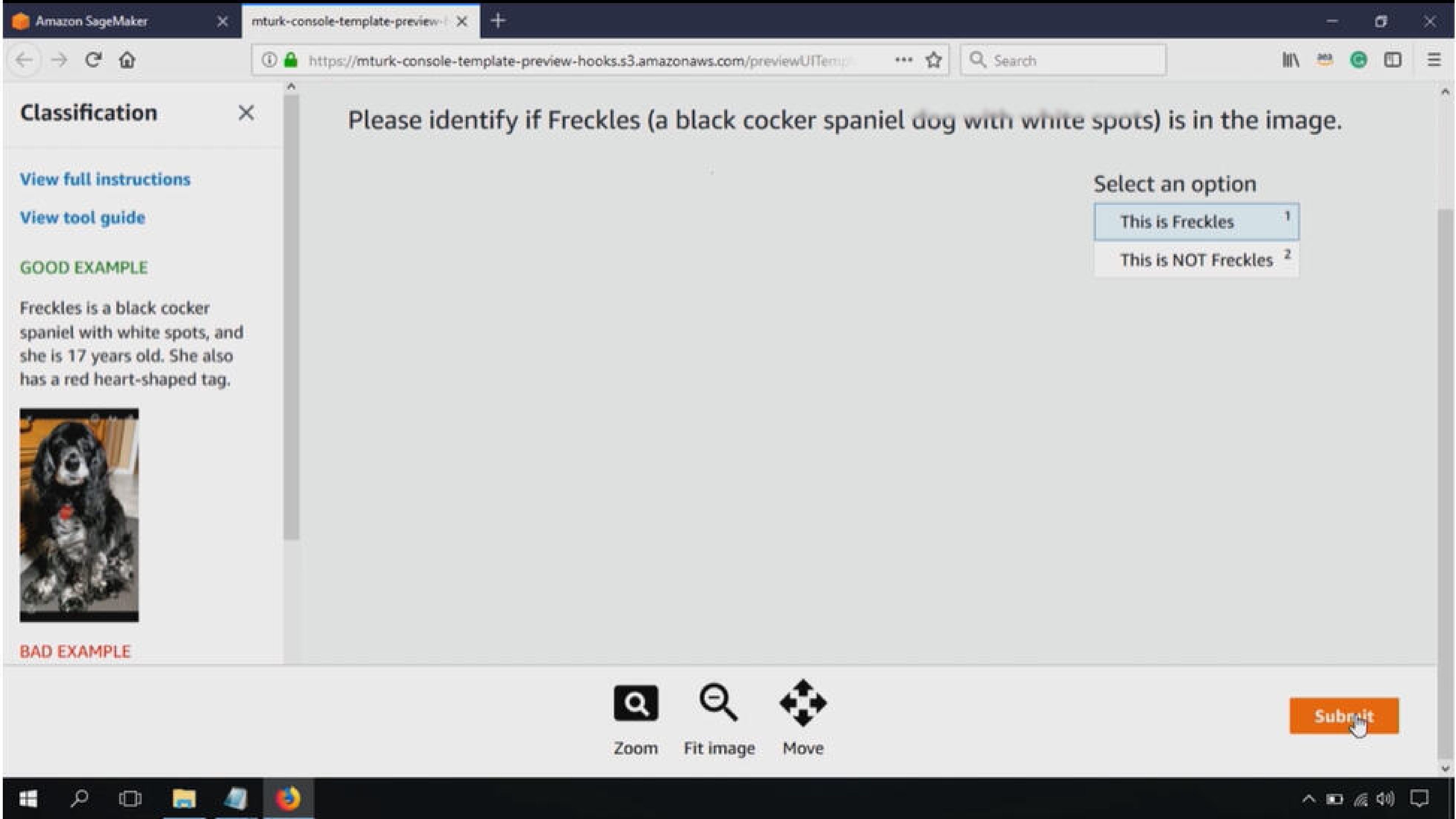
GOOD EXAMPLE

Freckles is a black cocker spaniel with white spots, and she is 17 years old. She also has a red heart-shaped tag.

BAD EXAMPLE

Please make sure to mark dogs that are not Freckles as "This is NOT Freckles".

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Classification
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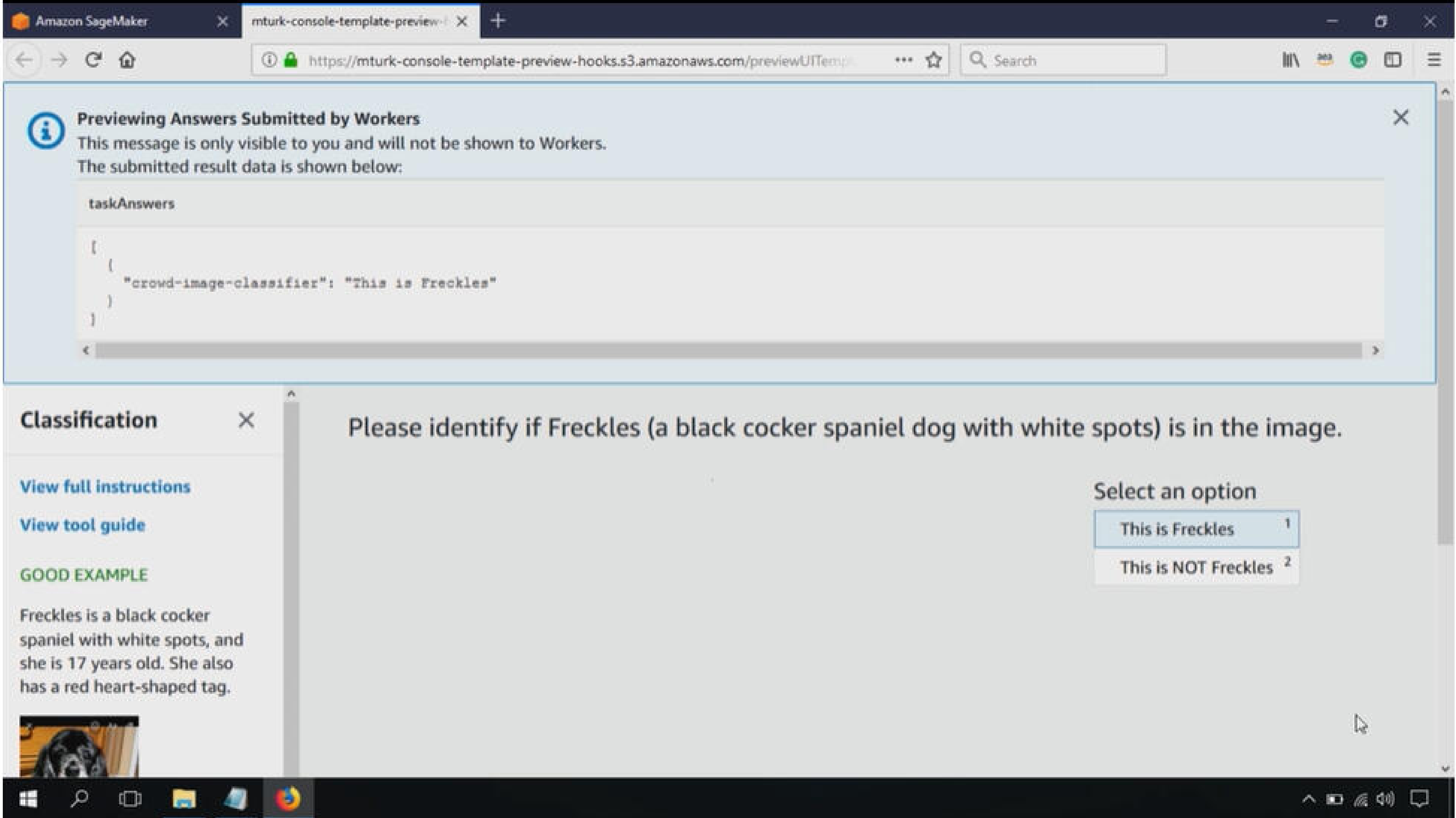
View tool guide
GOOD EXAMPLE
Freckles is a black cocker spaniel with white spots, and she is 17 years old. She also has a red heart-shaped tag.
BAD EXAMPLE
Please identify if Freckles (a black cocker spaniel dog with white spots) is in the image.
Select an option
This is Freckles 1
This is NOT Freckles 2
Zoom
Fit image
Move
Submit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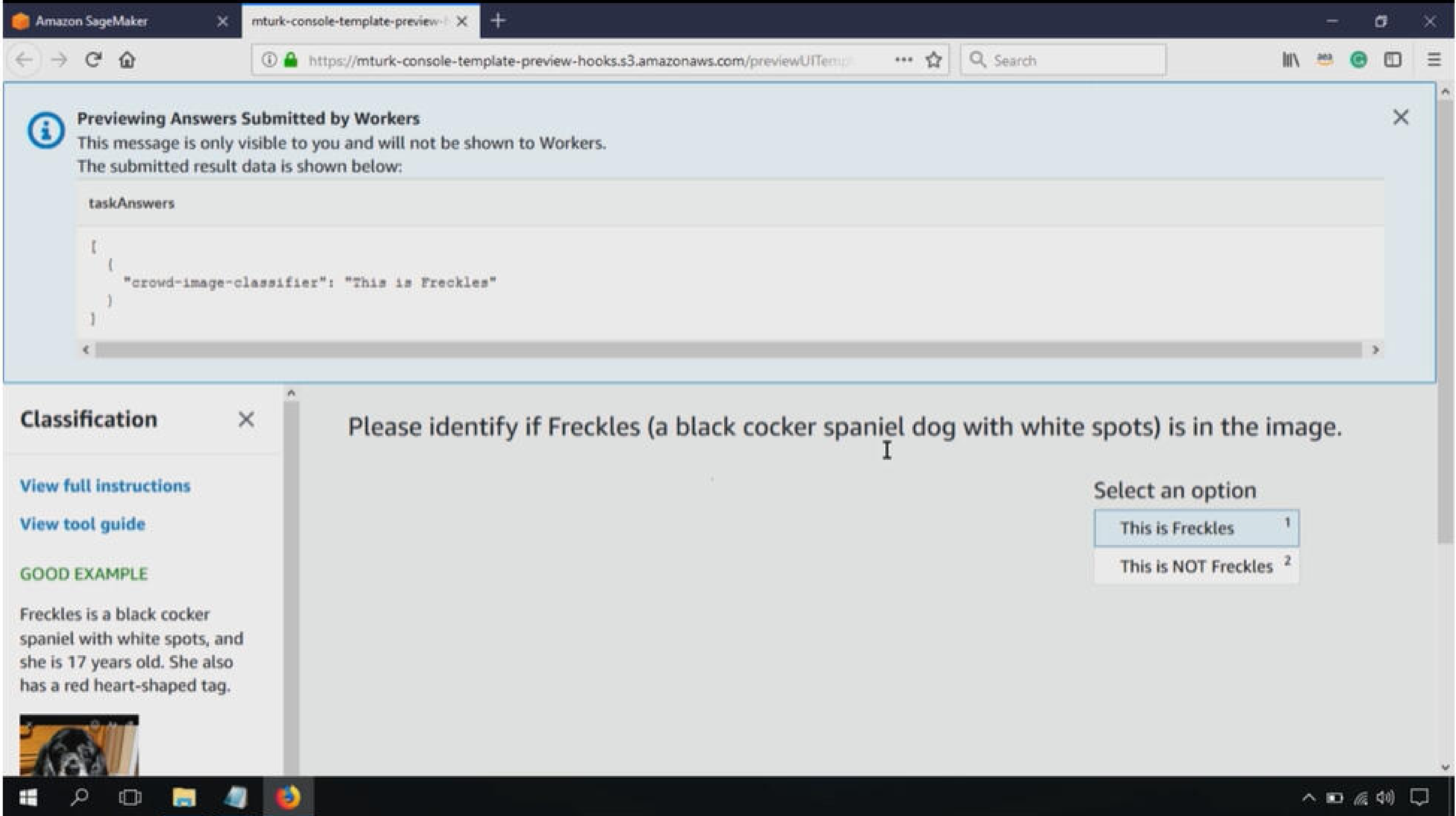
https://mturk-console-template-preview-hooks.s3.amazonaws.com/previewUITem
Search
Previewing Answers Submitted by Workers
This message is only visible to you and will not be shown to Workers.
The submitted result data is shown below:
taskAnswers
[
{
"crowd-image-classifier": "This is Freckles"
}
]
Classification
View full instructions
View tool guide
GOOD EXAMPLE
Freckles is a black cocker spaniel with white spots, and she is 17 years old. She also has a red heart-shaped tag.
Please identify if Freckles (a black cocker spaniel dog with white spots) is in the image.
Select an option
This is Freckles 1
This is NOT Freckles 2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https://mturk-console-template-preview-hooks.s3.amazonaws.com/previewUITem
Search
Previewing Answers Submitted by Workers
This message is only visible to you and will not be shown to Workers.
The submitted result data is shown below:
taskAnswers
[
{
"crowd-image-classifier": "This is Freckles"
}
]
Classification
View full instructions
View tool guide
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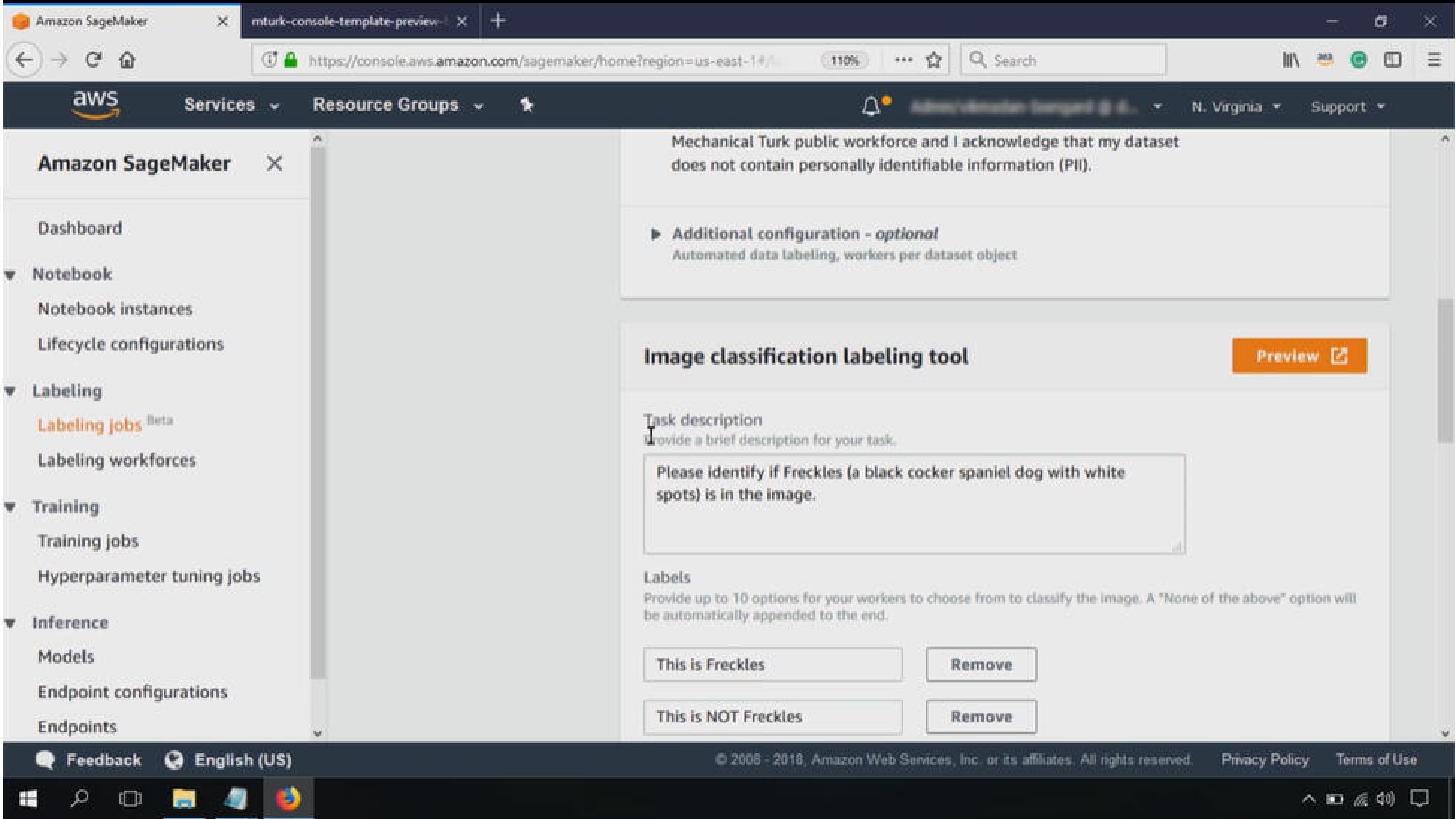
Freckles is a black cocker spaniel with white spots, and she is 17 years old. She also has a red heart-shaped tag.
Please identify if Freckles (a black cocker spaniel dog with white spots) is in the image.
Select an option
This is Freckles 1
This is NOT Freckles 2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Mechanical Turk public workforce and I acknowledge that my dataset does not contain personally identifiable information (PII).
Additional configuration - optional
Automated data labeling, workers per dataset object
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Preview
Task description
Provide a brief description for your task.
Please identify if Freckles (a black cocker spaniel dog with white spots) is in the image.
Labels
Provide up to 10 options for your workers to choose from to classify the image. A "None of the above" option will be automatically appended to the end.
This is Freckles
Remove
This is NOT Freckles
Remove
Feedback
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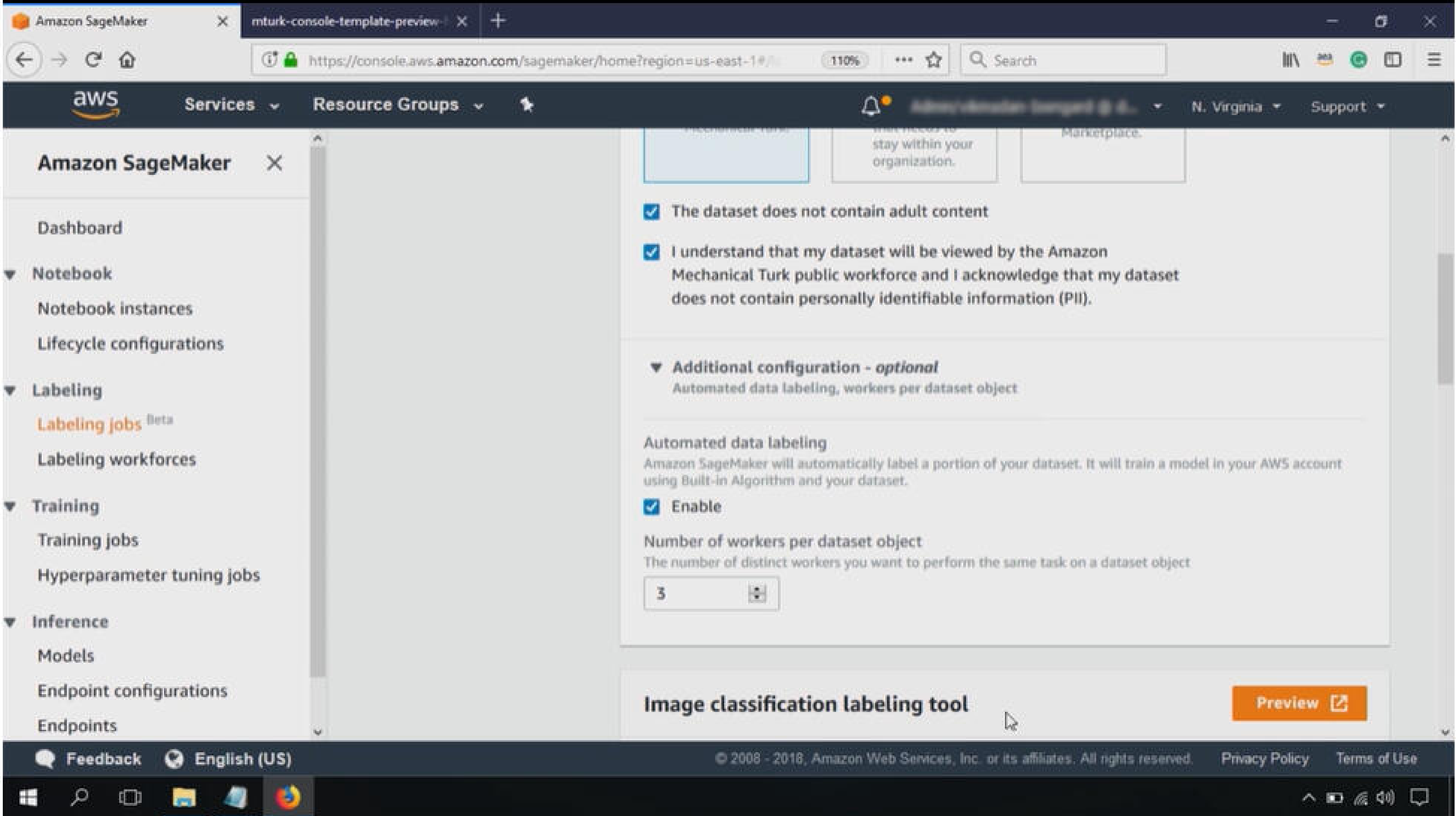

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stay within your organization.
Marketplace.
The dataset does not contain adult content
I understand that my dataset will be viewed by the Amazon Mechanical Turk public workforce and I acknowledge that my dataset does not contain personally identifiable information (PII).
Additional configuration - optional
Automated data labeling, workers per dataset object
Automated data labeling
Amazon SageMaker will automatically label a portion of your dataset. It will train a model in your AWS account using Built-in Algorithm and your dataset.
Enable
Number of workers per dataset object
The number of distinct workers you want to perform the same task on a dataset object
3
Image classification labeling tool
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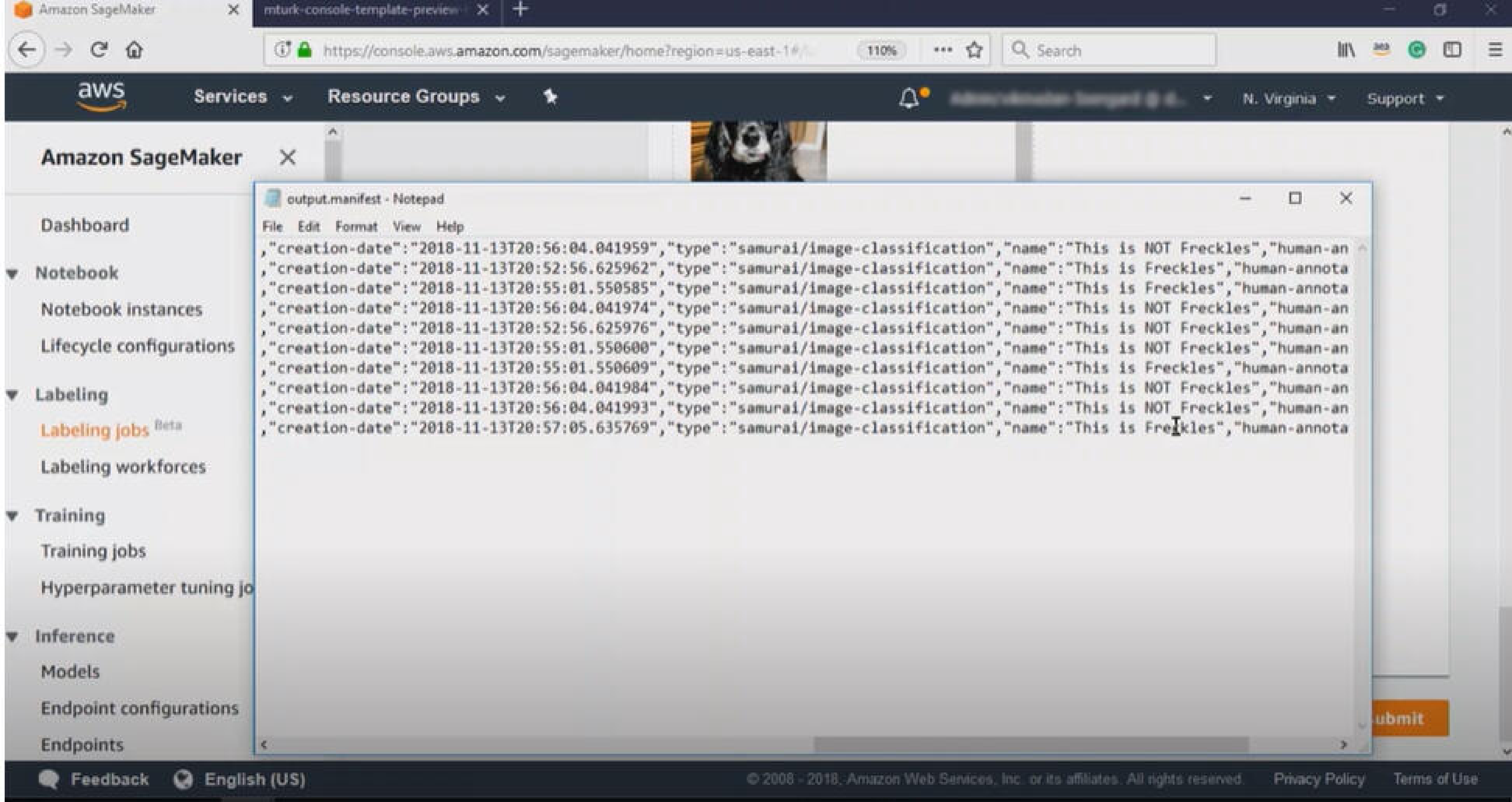
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output.manifest - Notepad
File Edit Format View Help
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,"creation-date":"2018-11-13T20:52:56.625962","type":"samurai/image-classification","name":"This is Freckles","human-annota
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,"creation-date":"2018-11-13T20:57:05.635769","type":"samurai/image-classification","name":"This is Freckles","human-annota
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Amazon Polly

Presented by Jorge Negron

aws training and certification

Introduction

- Text to Speech Service Introduction
- Amazon Polly Overview
- Amazon Polly Use Cases
- AWS Console Demonstration

Artificial Intelligence Services

aws training and certification

- Amazon Lex: Build Voice and Text Chatbots
- **Amazon Polly: Turn Text into Lifelike Speech**
- Amazon Rekognition: Search and Analyze Images
- Amazon Machine Learning: Build Smart Applications

Amazon Polly

- Create applications that talk and increase accessibility
- Provides an easy to use and device independent solution
- Voices are high quality and as good as natural human speech
- Supports 24 languages with multiple voices per language
- Store and distribute the generated speech as an audio file

Amazon Polly

- Create applications that talk and increase accessibility
- Provides an easy to use and device independent solution
- Voices are high quality and as good as natural human speech
- Supports 24 languages with multiple voices per language
- Store and distribute the generated speech as an audio file

Amazon Polly

aws training and certification

- Accurate text processing.
- Highly Intelligible.
- Supports Speech Synthesis Markup Language (SSML).
- Supports dictionaries (Lexicons) for custom pronunciation.
- Natural sounding speech generation from text.

Amazon Polly and SSML

- Speech Synthesis Markup Language (SSML)
- XML based markup language. Tags comply with SSML 1.1
- SSML start with **<speak>**, end with **</speak>**
- Modify aspects of the speech output:
  - Expansion of abbreviations and acronyms
  - Control of pitch, volume, and speed of speech

Amazon Polly and SSML

- Speech Synthesis Markup Language (SSML)
- XML based markup language. Tags comply with SSML 1.1
- SSML start with **<speak>**, end with **</speak>**
- Modify aspects of the speech output:
  - Expansion of abbreviations and acronyms
  - Control of pitch, volume, and speed of speech

Amazon Polly Use Cases

Amazon Polly Use Cases

- Education: Language learning applications (24 languages)
- Gaming: Test in-game dialogs without needing a voice actor
- Content Creation: Read news channel content aloud
- Telephony: Generated speech is used as Voice Response

Amazon Polly Use Cases

aws training and certification

- Education: Language learning applications (24 languages)
- Gaming: Test in-game dialogs without needing a voice actor
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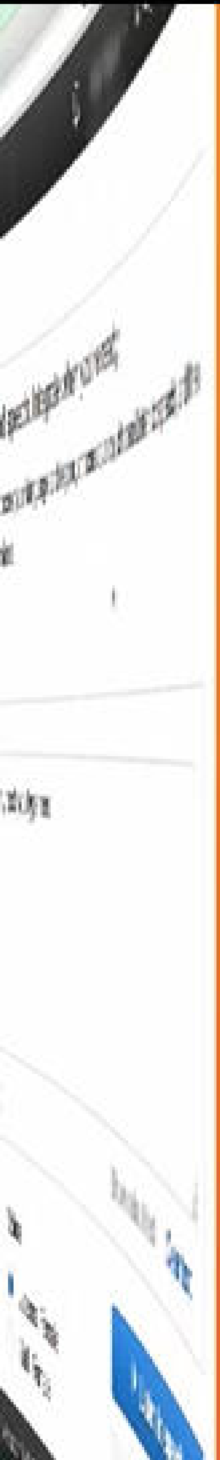
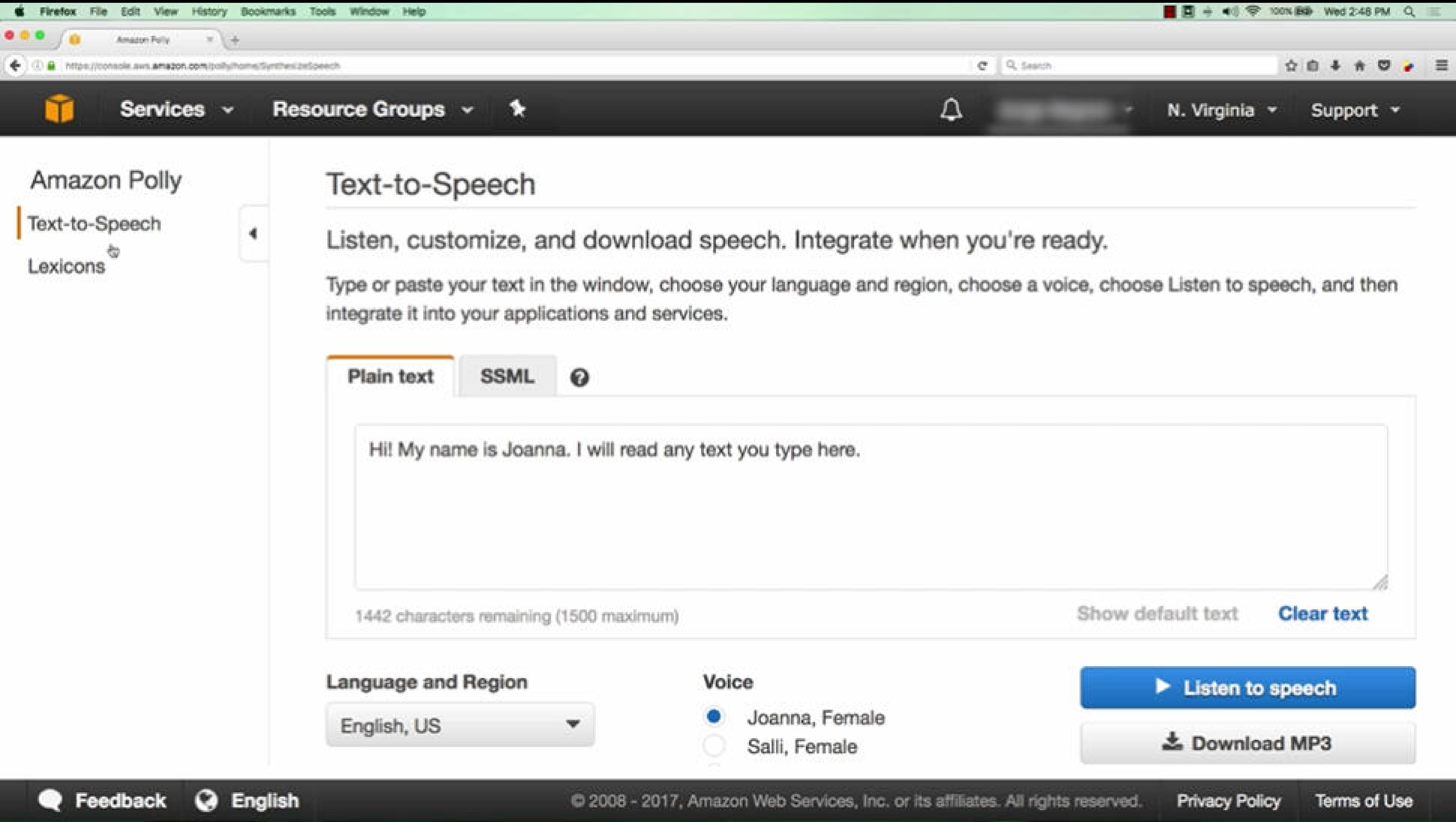


Amazon Polly Demonstration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Plain text
SSML
Hi! My name is Joanna. I will read any text you type here.
1442 characters remaining (1500 maximum)
Show default text
Clear text
Language and Region
English, US
Voice
Joanna, Female
Salli, Female
Listen to speech
Download MP3
Feedback
English
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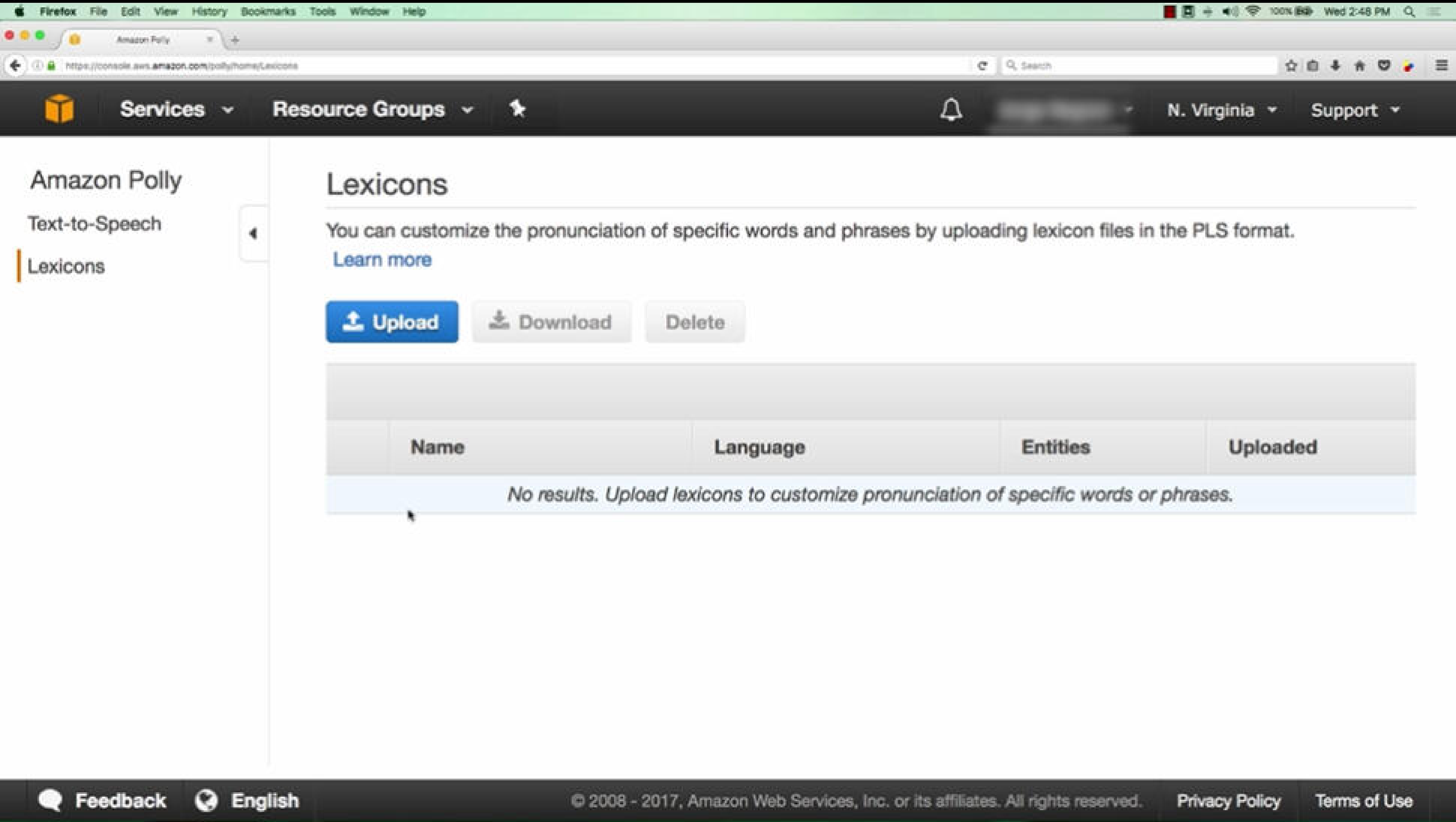

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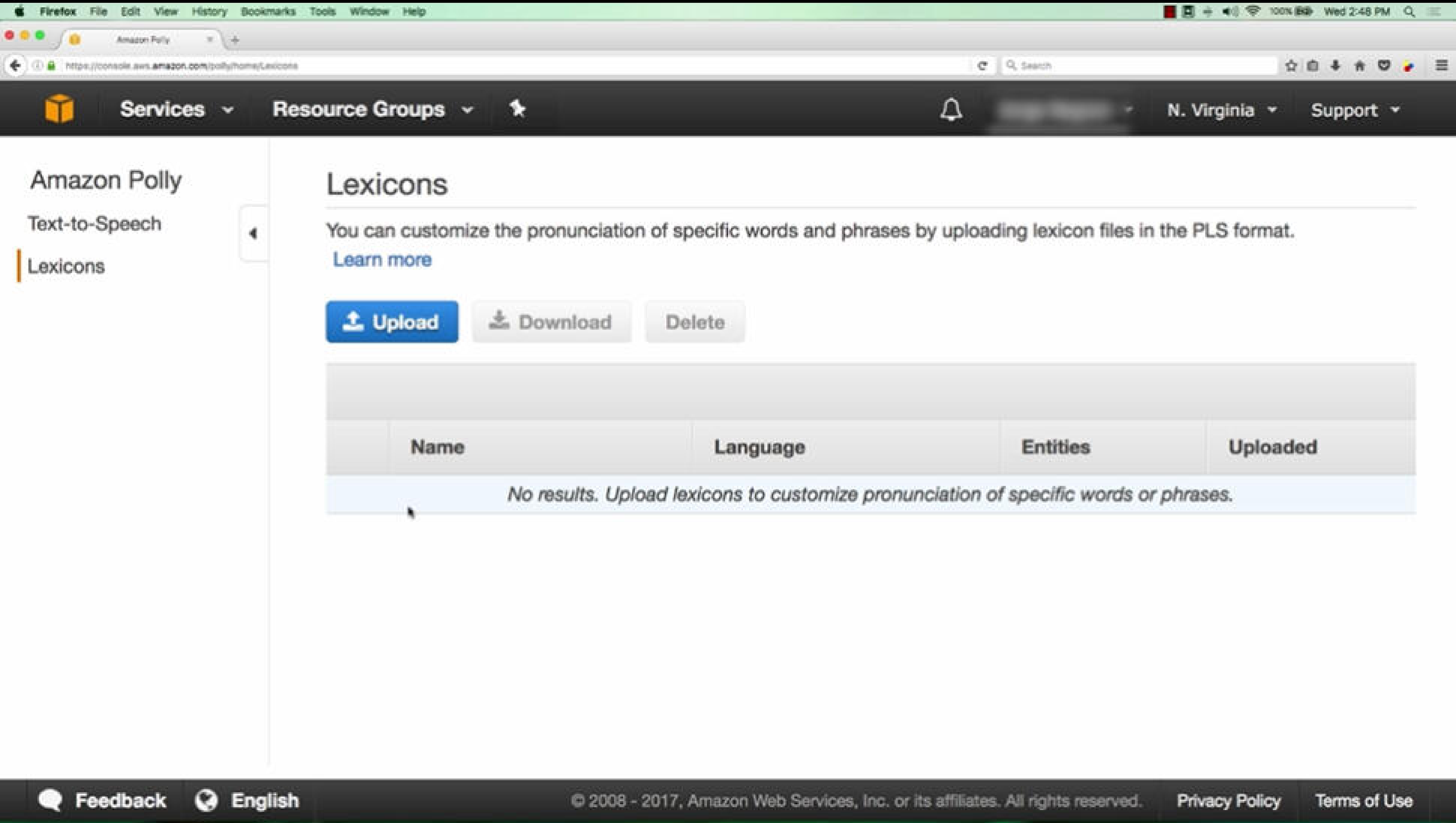
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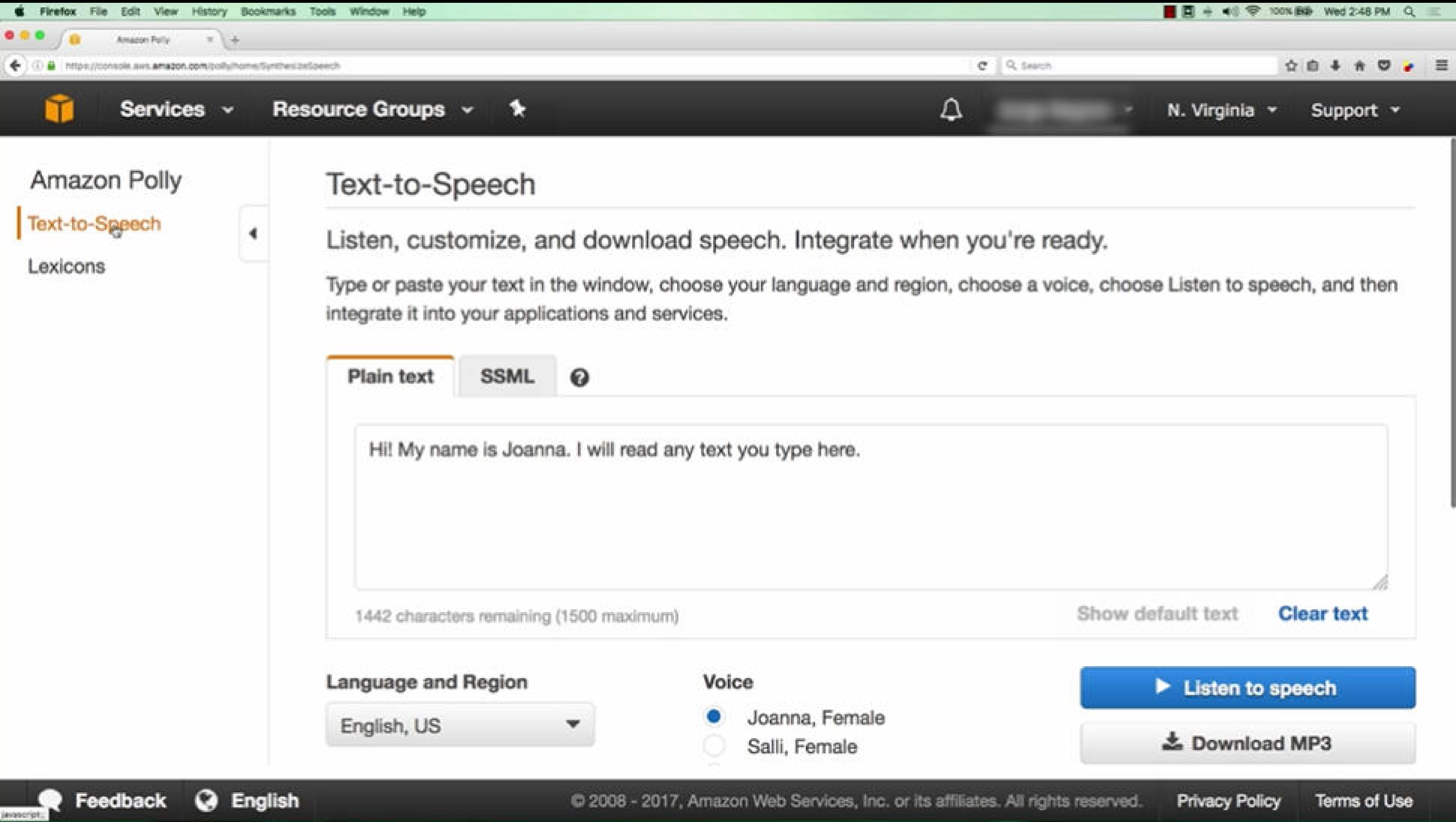
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Clear text
Language and Region
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Voice
Joanna, Female
Salli, Female
Listen to speech
Download MP3
Feedback
English
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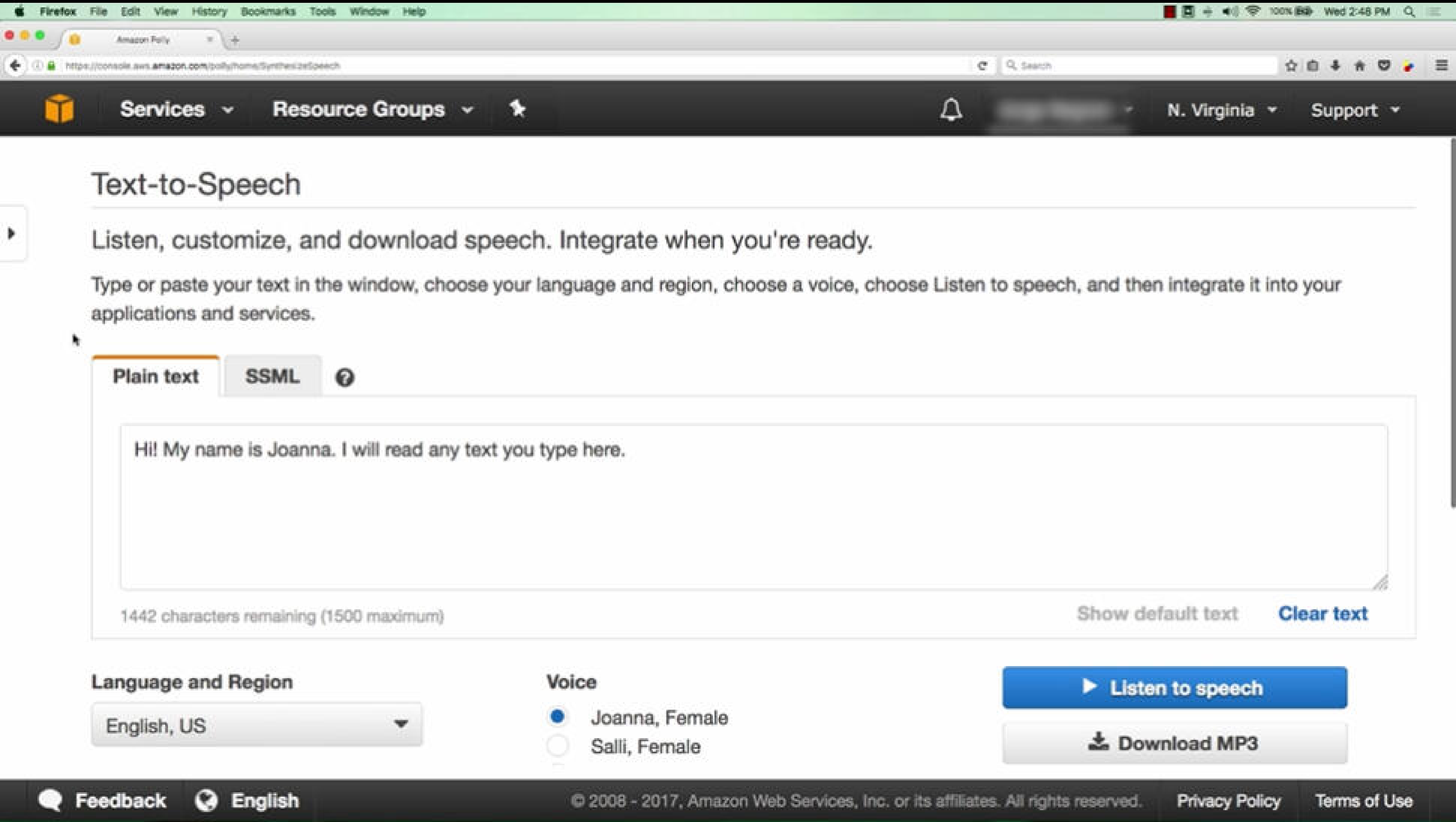
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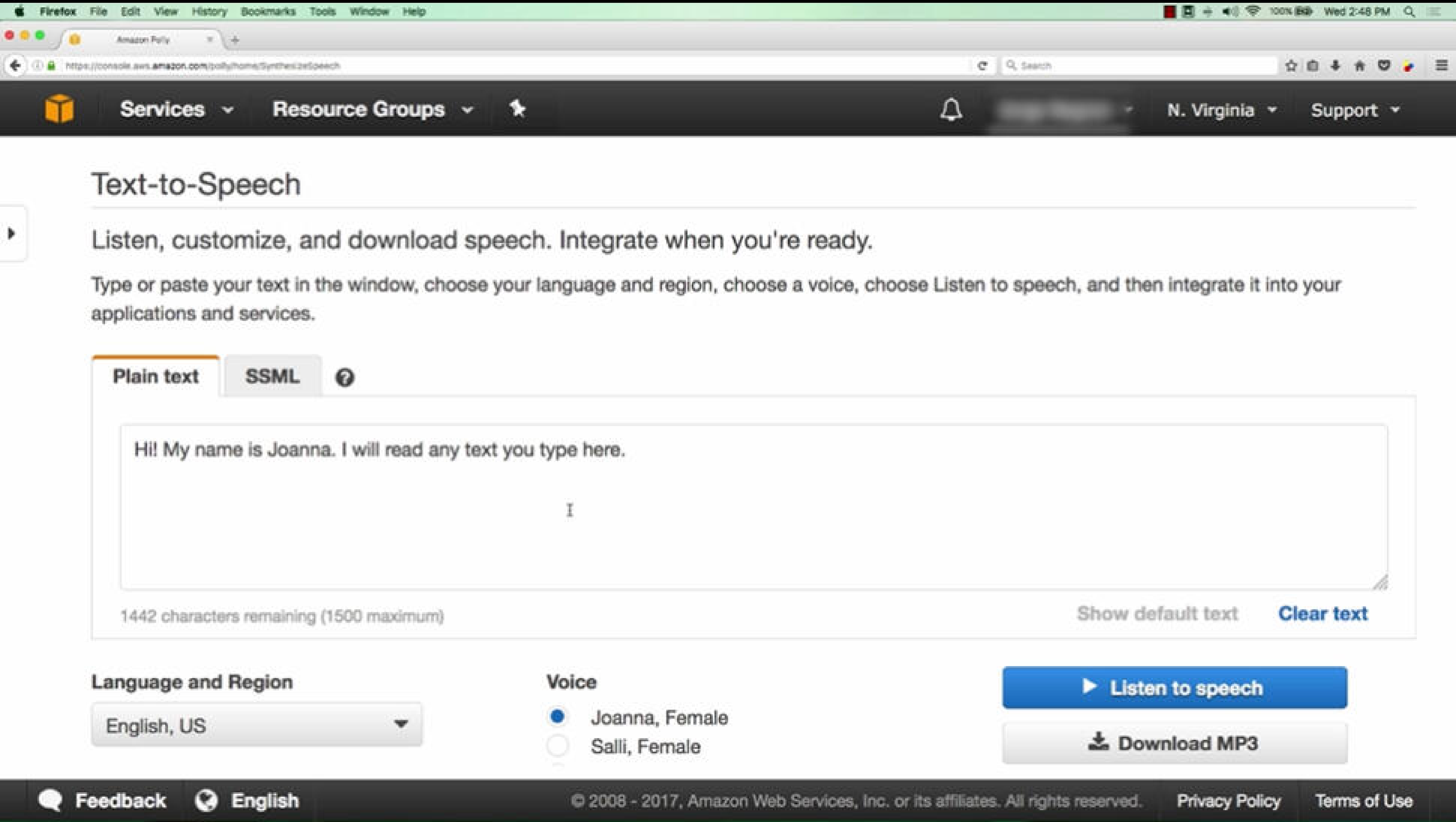
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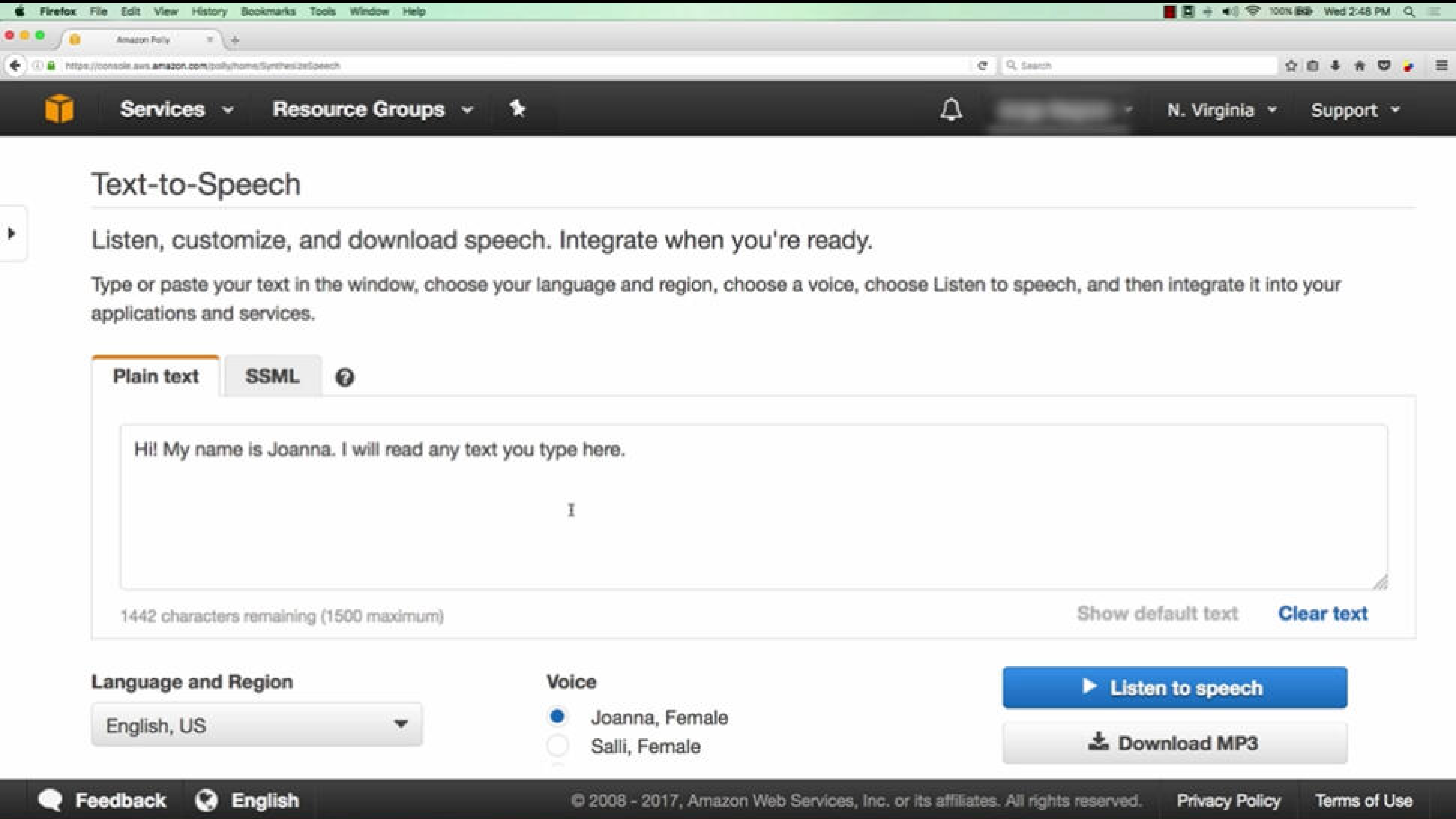
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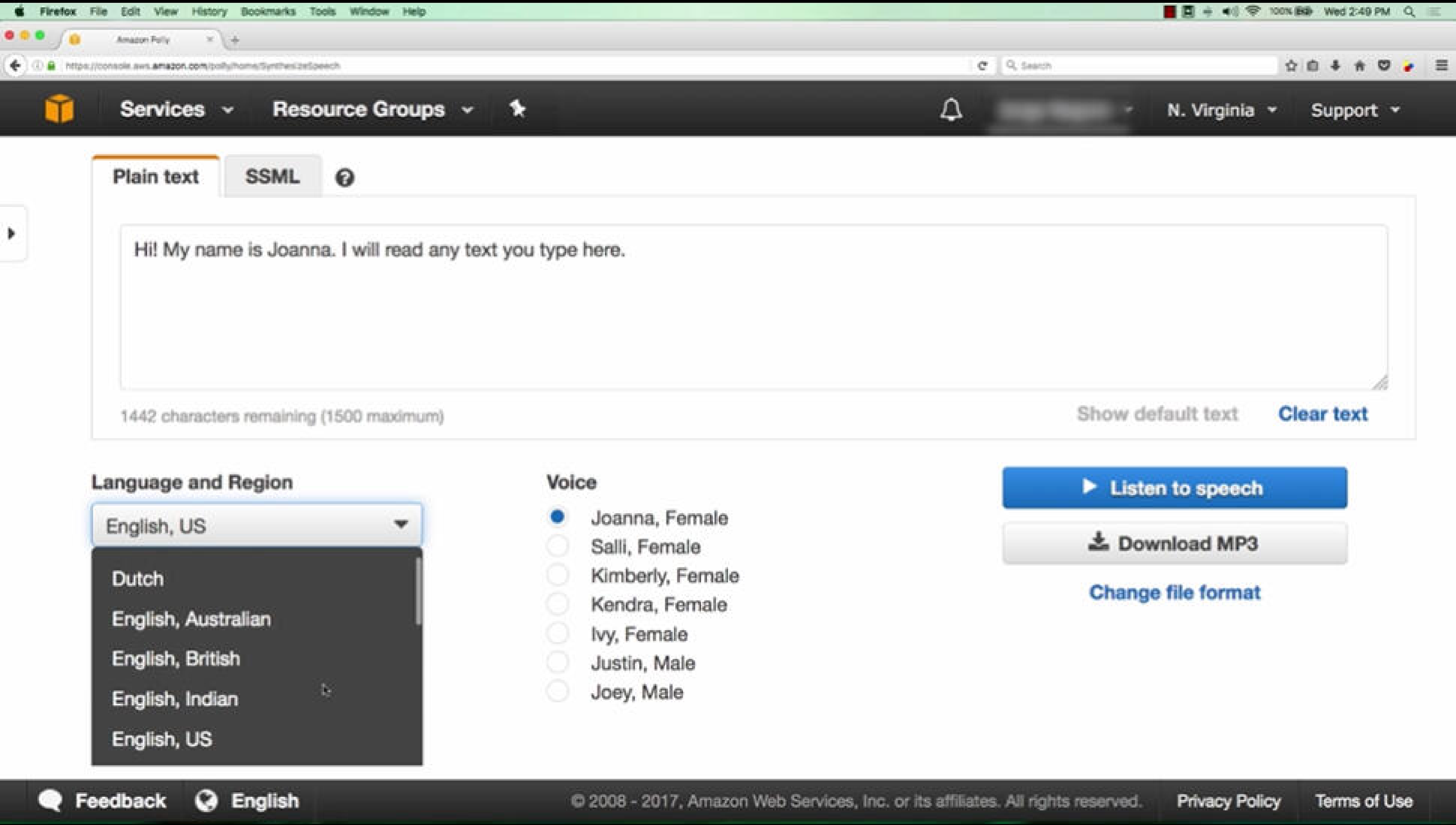
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Plain text
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Hi! My name is Joanna. I will read any text you type here.
1442 characters remaining (1500 maximum)
Show default text
Clear text
Language and Region
English, US
Dutch
English, Australian
English, British
English, Indian
English, US
Voice
Joanna, Female
Salli, Female
Kimberly, Female
Kendra, Female
Ivy, Female
Justin, Male
Joey, Male
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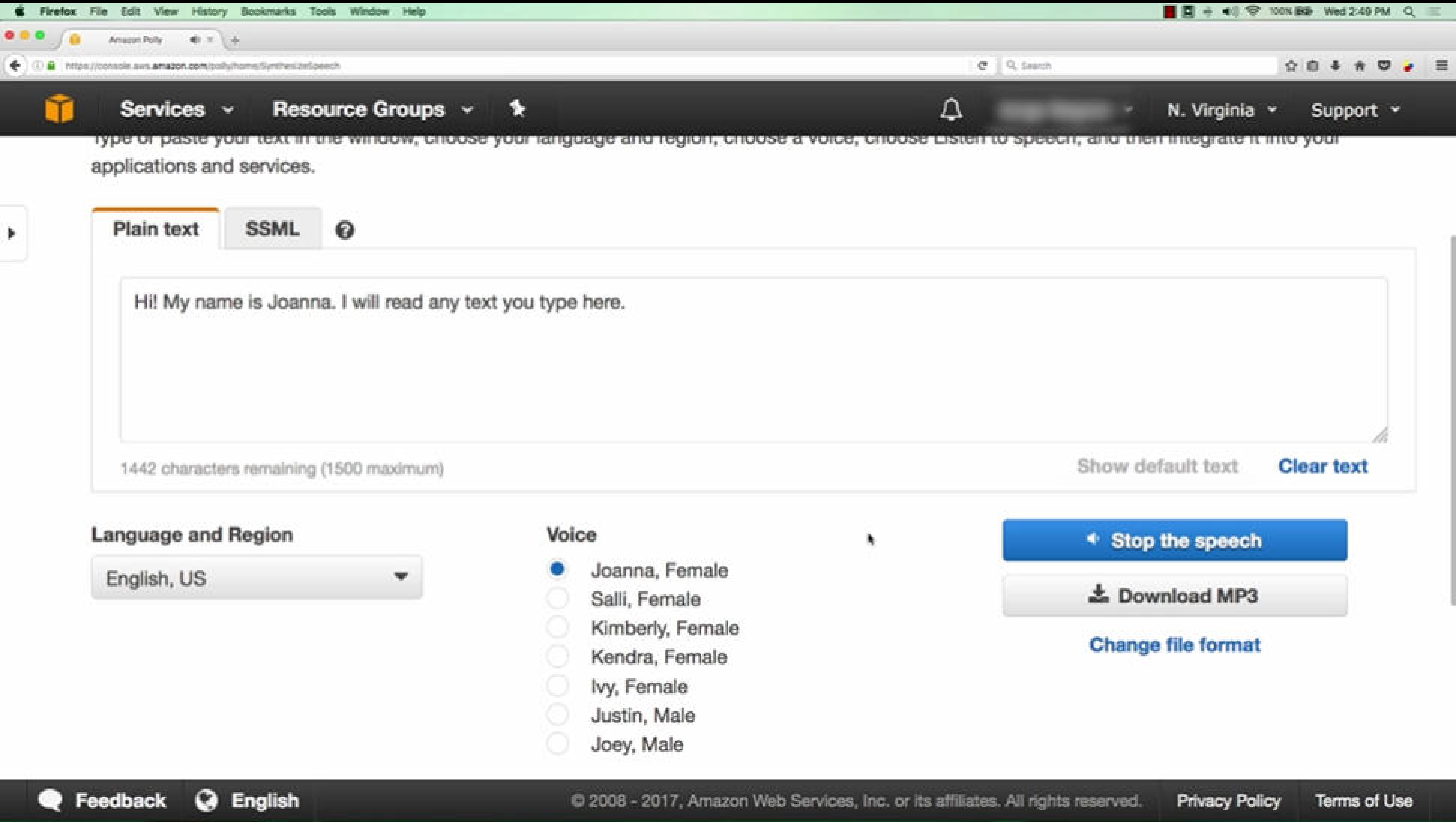
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Salli, Female
Kimberly, Female
Kendra, Female
Ivy, Female
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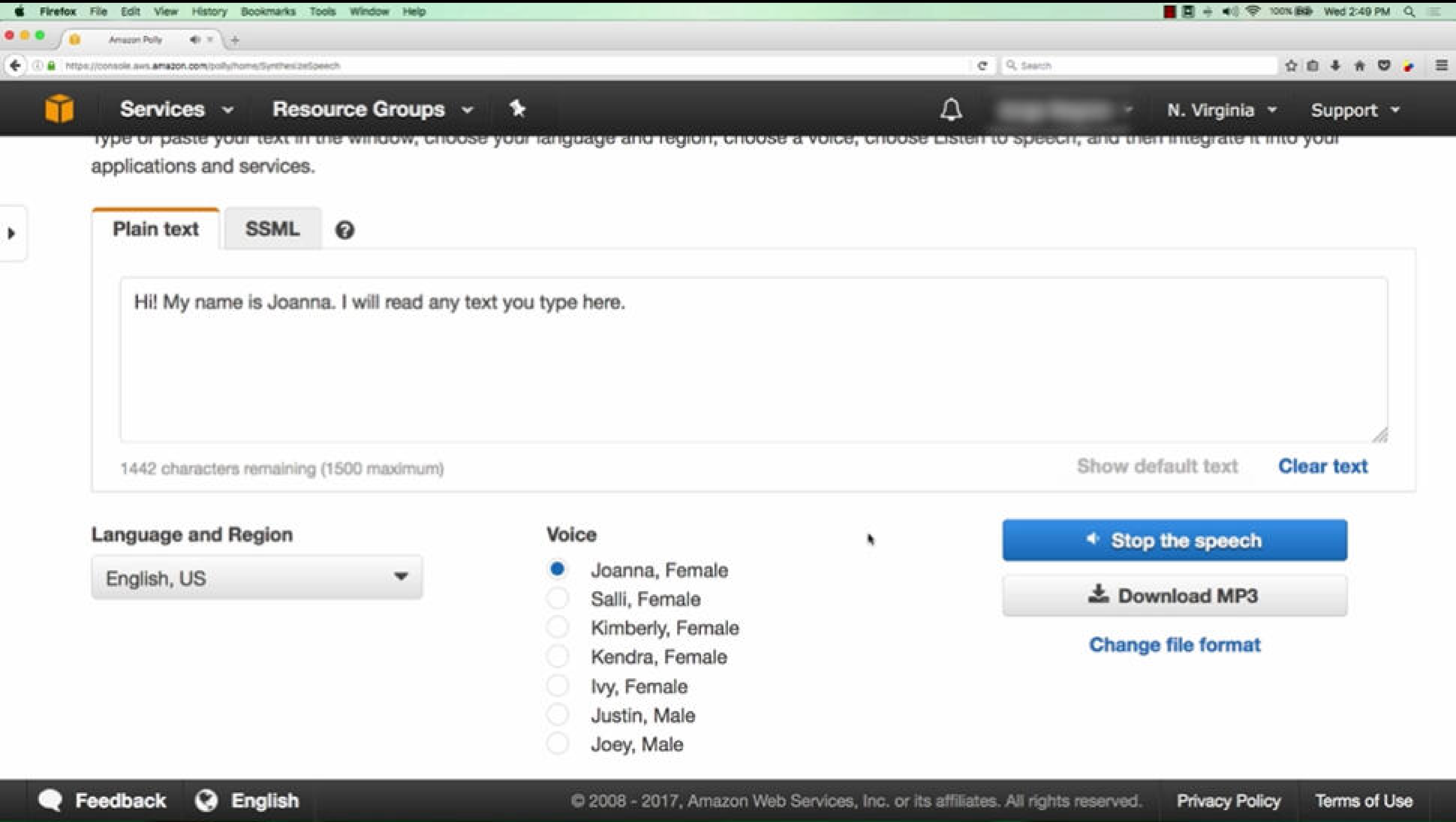
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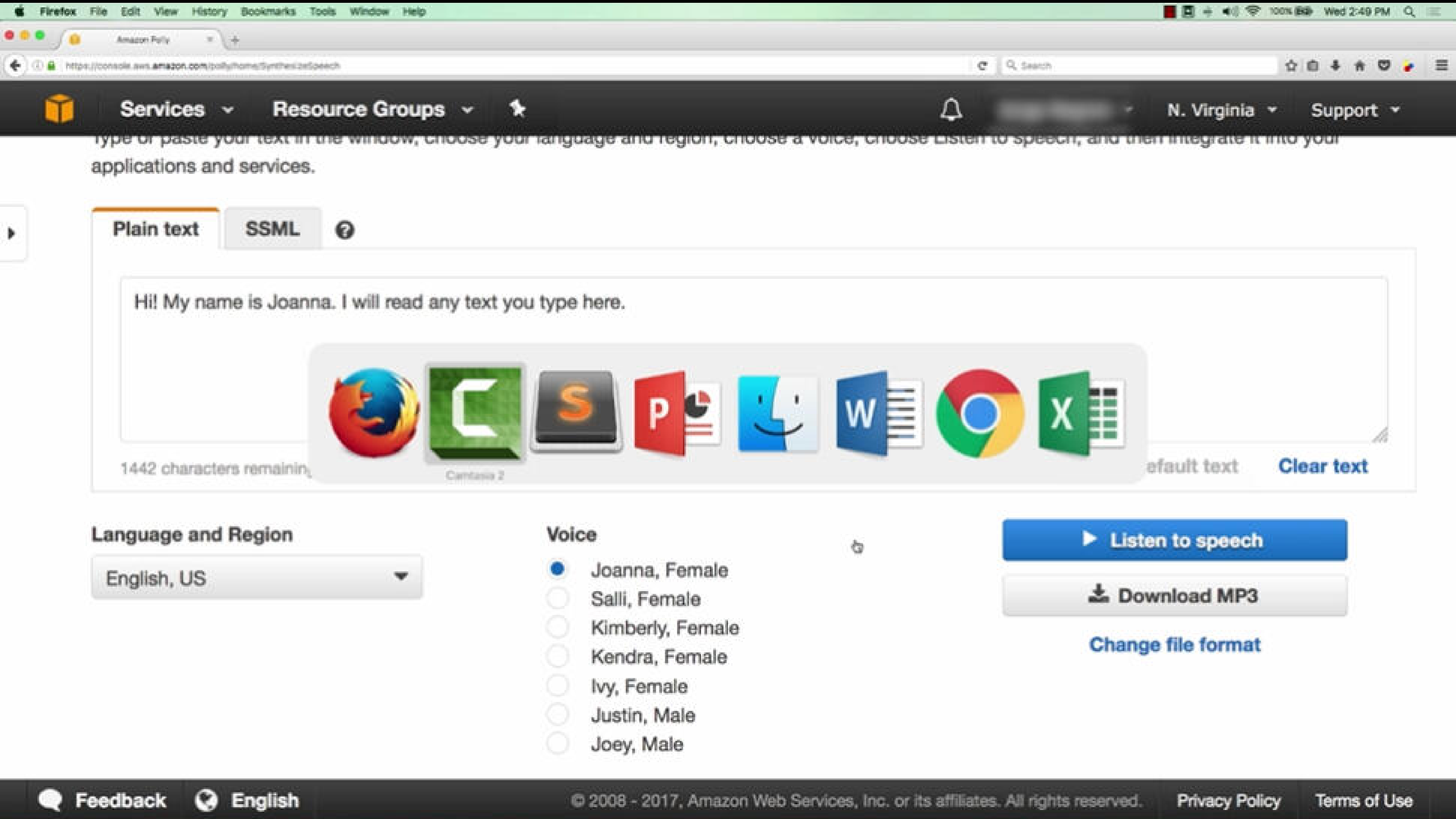
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Plain text
SSML
Hi! My name is Joanna. I will read any text you type here.
Camtasia 2
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efault text
Clear text
Language and Region
English, US
Voice
Joanna, Female
Salli, Female
Kimberly, Female
Kendra, Female
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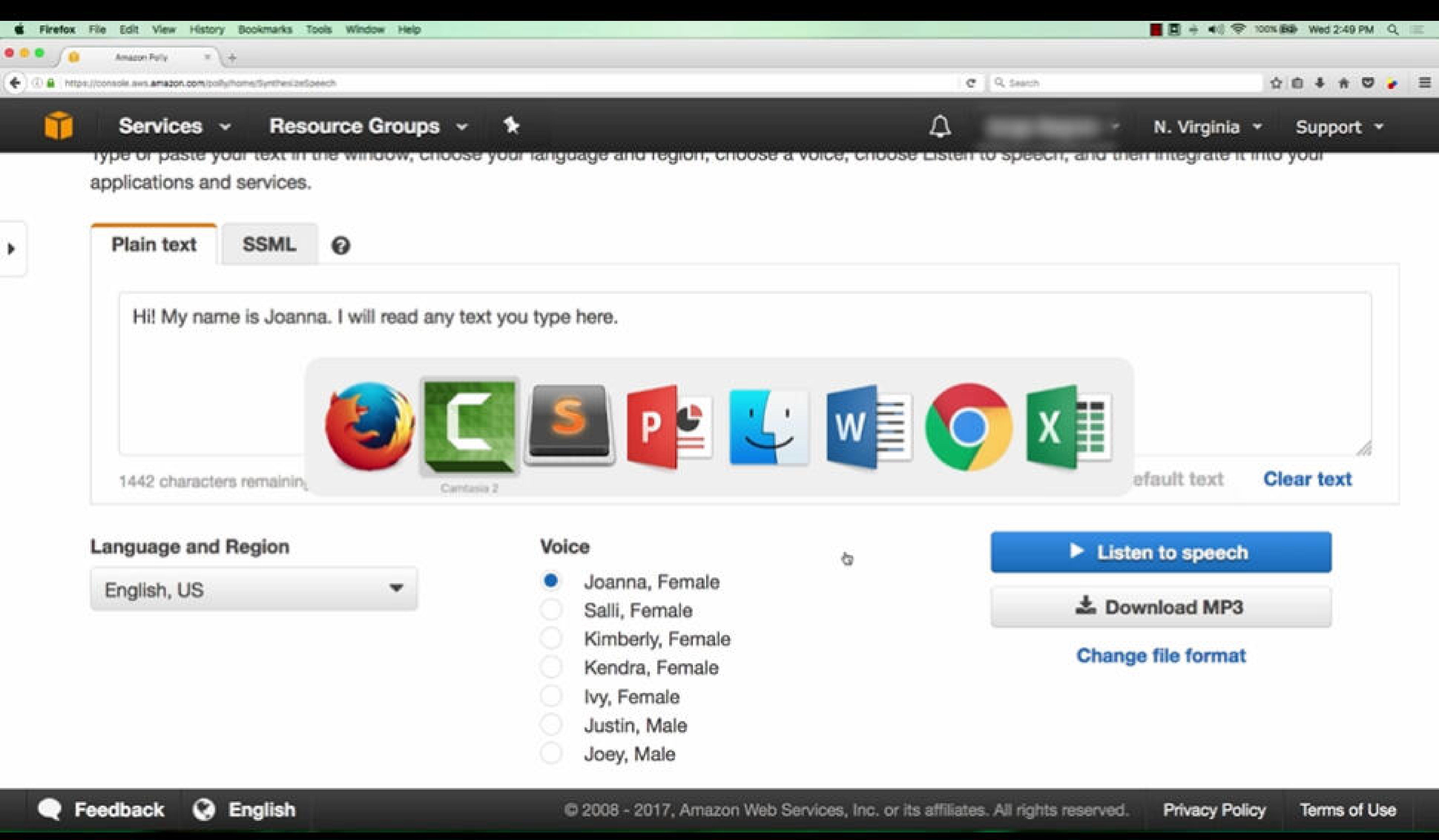

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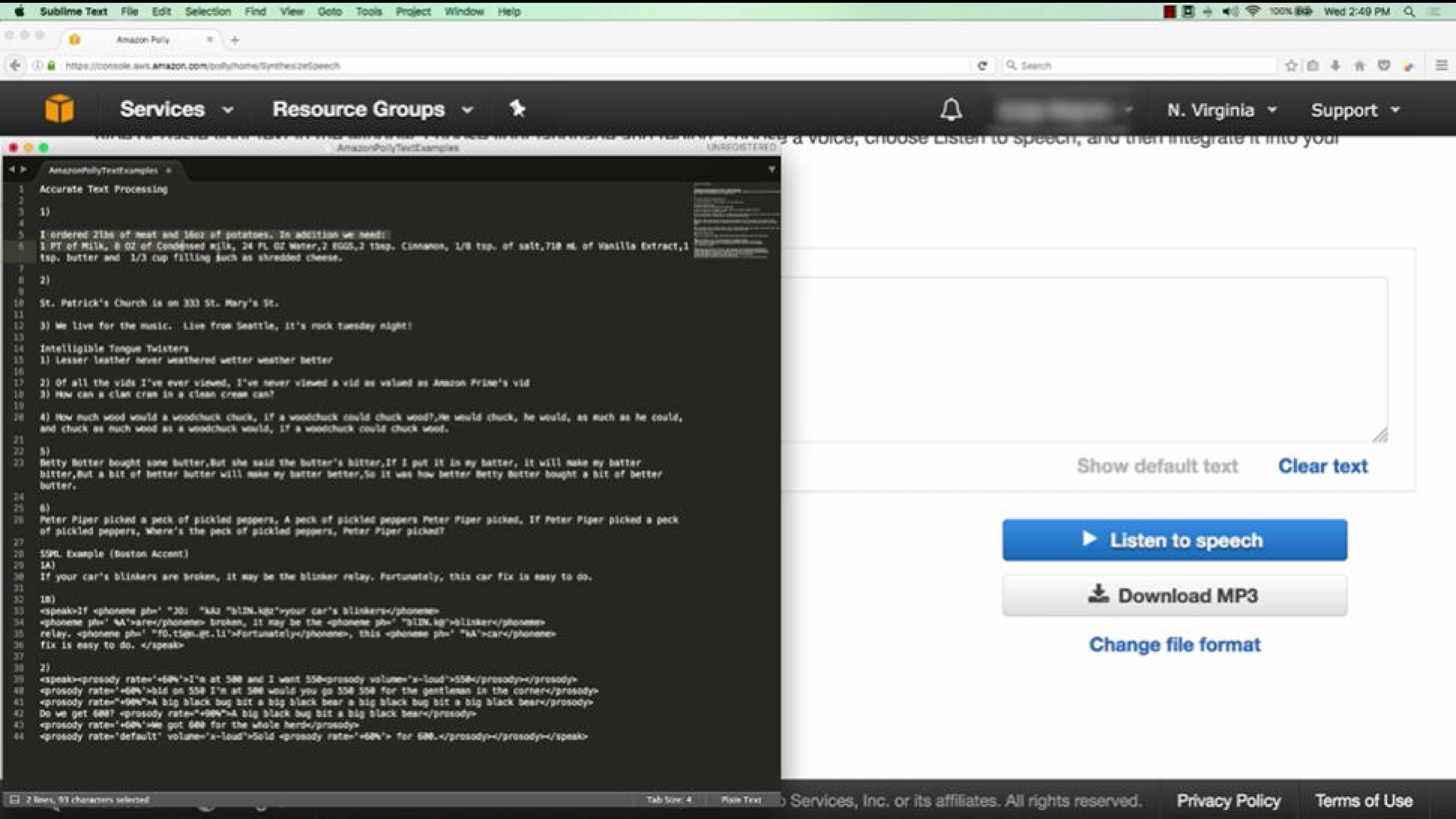

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AmazonPollyTextExamples
UNREGISTERED
Accurate Text Processing
1)
I ordered 2lbs of meat and 16oz of potatoes. In addition we need:
1 PT of Milk, 8 OZ of Condensed milk, 24 FL OZ Water,2 EGGS,2 tbsp. Cinnamon, 1/8 tsp. of salt,710 mL of Vanilla Extract,1 tsp. butter and 1/3 cup filling such as shredded cheese.
2)
St. Patrick's Church is on 333 St. Mary's St.
3) We live for the music. Live from Seattle, it's rock tuesday night!
Intelligible Tongue Twisters
1) Lesser leather never weathered wetter weather better
2) Of all the vids I've ever viewed, I've never viewed a vid as valued as Amazon Prime's vid
3) How can a clam cram in a clean cream can?
4) How much wood would a woodchuck chuck, if a woodchuck could chuck wood?,He would chuck, he would, as much as he could, and chuck as much wood as a woodchuck would, if a woodchuck could chuck wood.
5)
Betty Botter bought some butter,But she said the butter's bitter,If I put it in my batter, it will make my batter bitter,But a bit of better butter will make my batter better,So it was how better Betty Botter bought a bit of better butter.
6)
Peter Piper picked a peck of pickled peppers, A peck of pickled peppers Peter Piper picked, If Peter Piper picked a peck of pickled peppers, Where's the peck of pickled peppers, Peter Piper picked?
SSML Example (Boston Accent)
1A)
If your car's blinkers are broken, it may be the blinker relay. Fortunately, this car fix is easy to do.
1B)
<speak>If <phoneme ph=' "JO: "kAz "blIN.k@z'>your car's blinkers</phoneme>
<phoneme ph=' %A'>are</phoneme> broken, it may be the <phoneme ph=' "blIN.k@'>blinker</phoneme>
relay. <phoneme ph=' "fO.tS@n.@t.li'>Fortunately</phoneme>, this <phoneme ph=' "kA'>car</phoneme>
fix is easy to do. </speak>
2)
<speak><prosody rate='+60%'>I'm at 500 and I want 550<prosody volume='x-loud'>550</prosody></prosody>
<prosody rate='+60%'>bid on 550 I'm at 500 would you go 550 550 for the gentleman in the corner</prosody>
<prosody rate="+90%">A big black bug bit a big black bear a big black bug bit a big black bear</prosody>
Do we get 600? <prosody rate="+90%">A big black bug bit a big black bear</prosody>
<prosody rate='+60%'>We got 600 for the whole herd</prosody>
<prosody rate='default' volume='x-loud'>Sold <prosody rate='+60%'> for 600.</prosody></prosody></speak>
2 lines, 93 characters selected
Tab Size: 4
Plain Text
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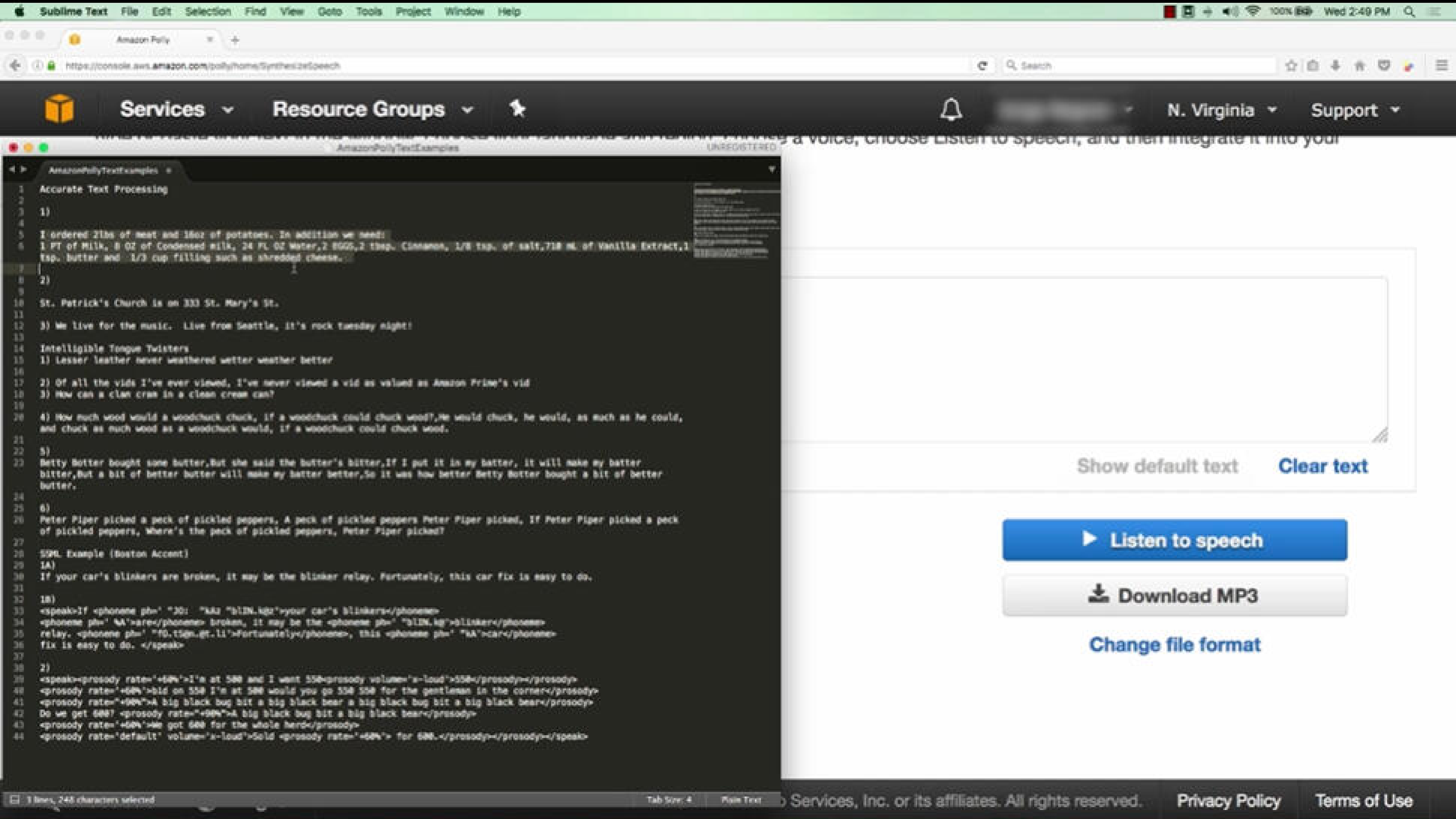
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1B)
fix is easy to do. </speak>
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<prosody rate='default' volume='x-loud'>Sold <prosody rate='+60%'> for 600.</prosody></prosody></speak>
3 lines, 248 characters selected
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Plain text | SSML

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1252 characters remaining (1500 maximum)

Show default text Clear text

Language and Region

English, US

Voice

- Joanna, Female
- Salli, Female
- Kimberly, Female
- Kendra, Female
- Ivy, Female
- Justin, Male
- Joey, Male

Listen to speech

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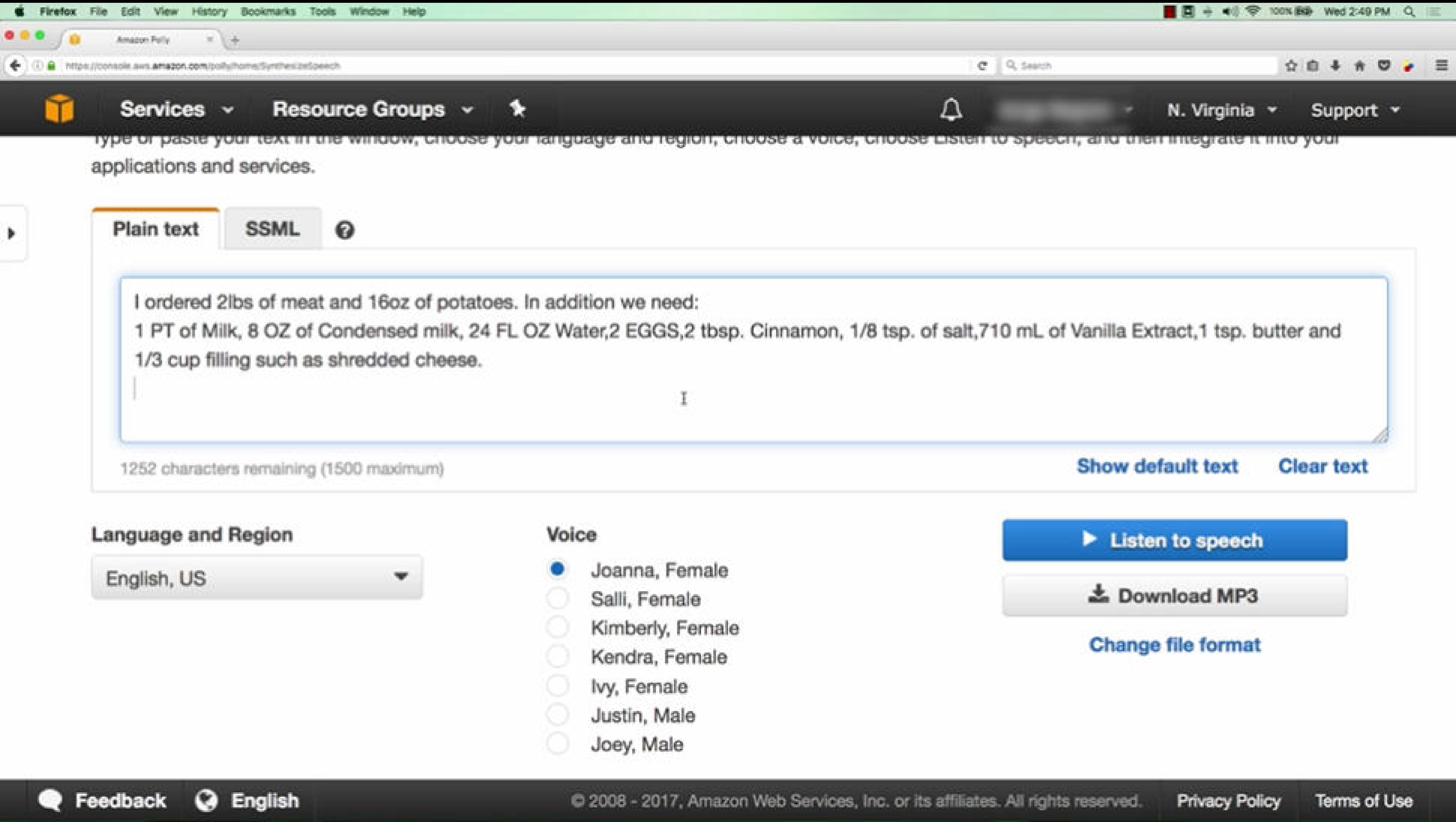
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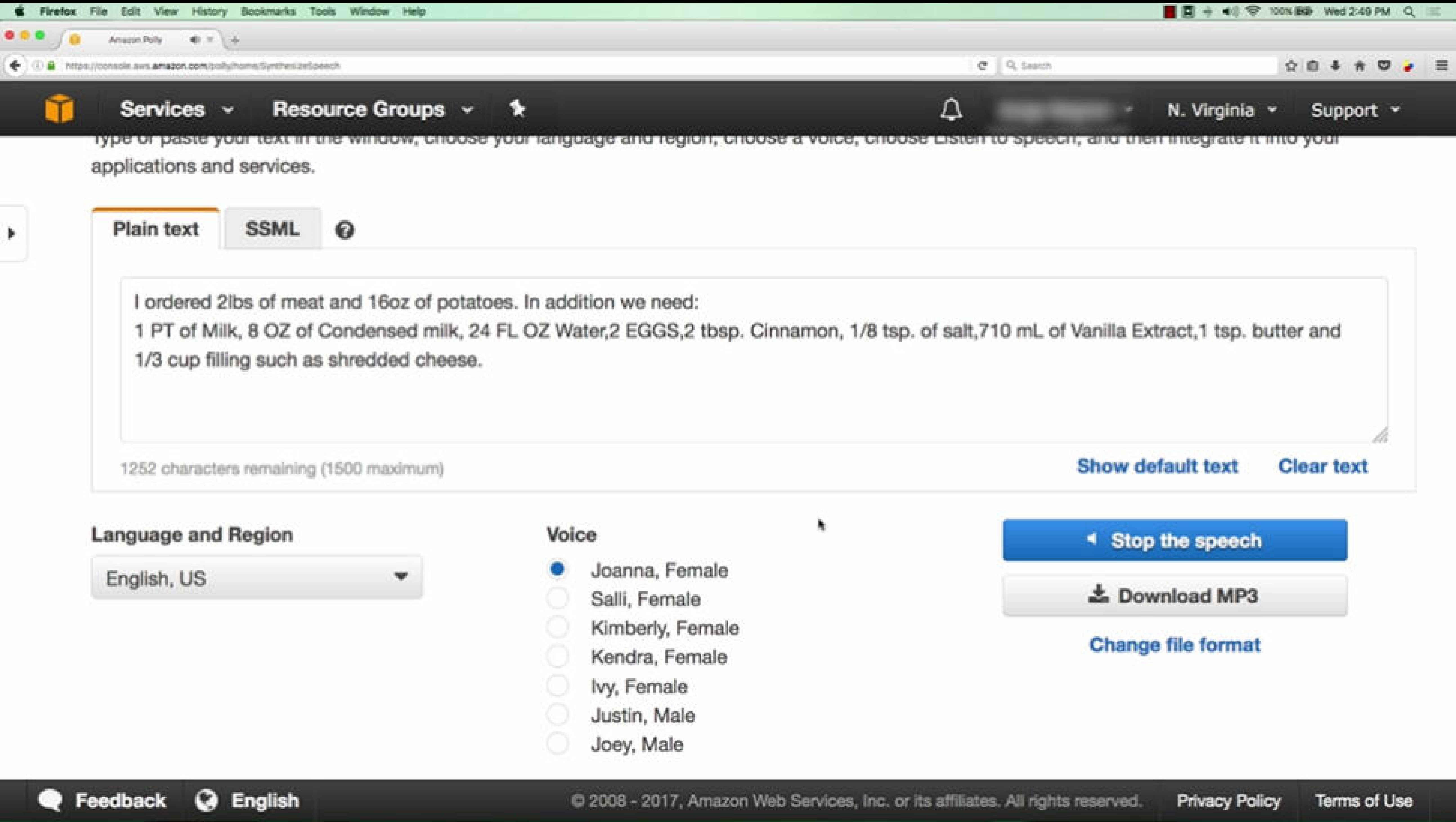
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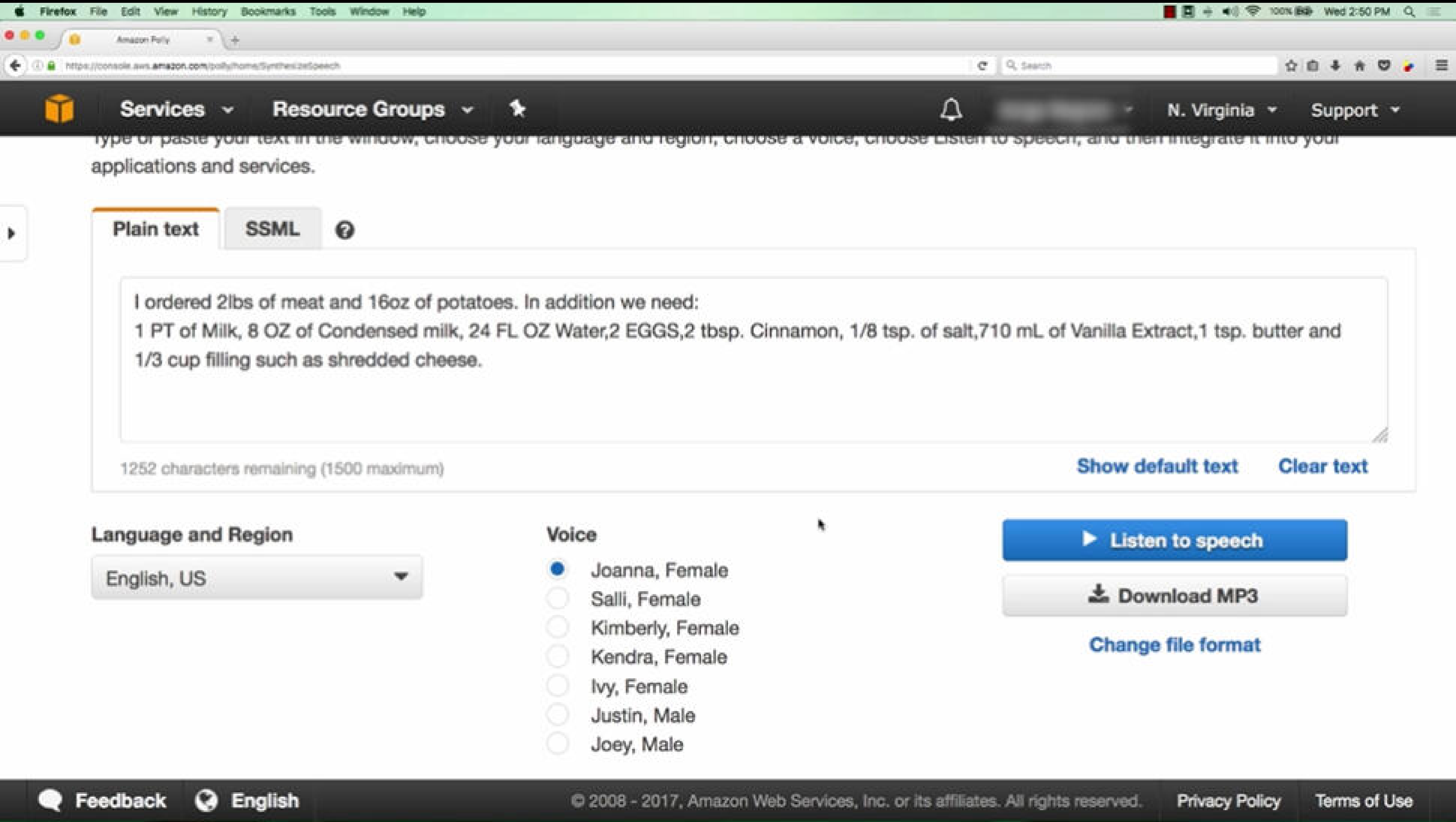
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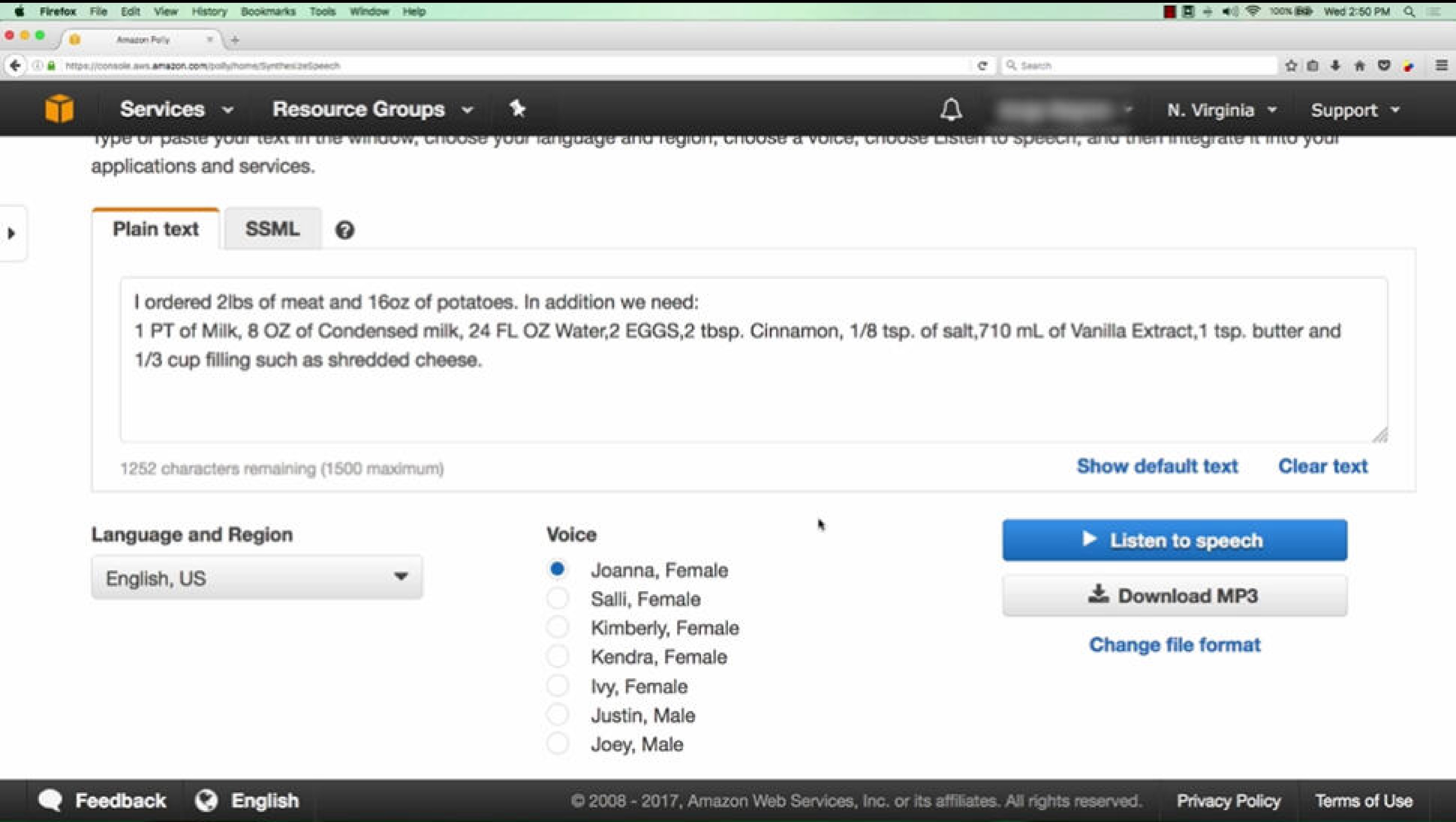

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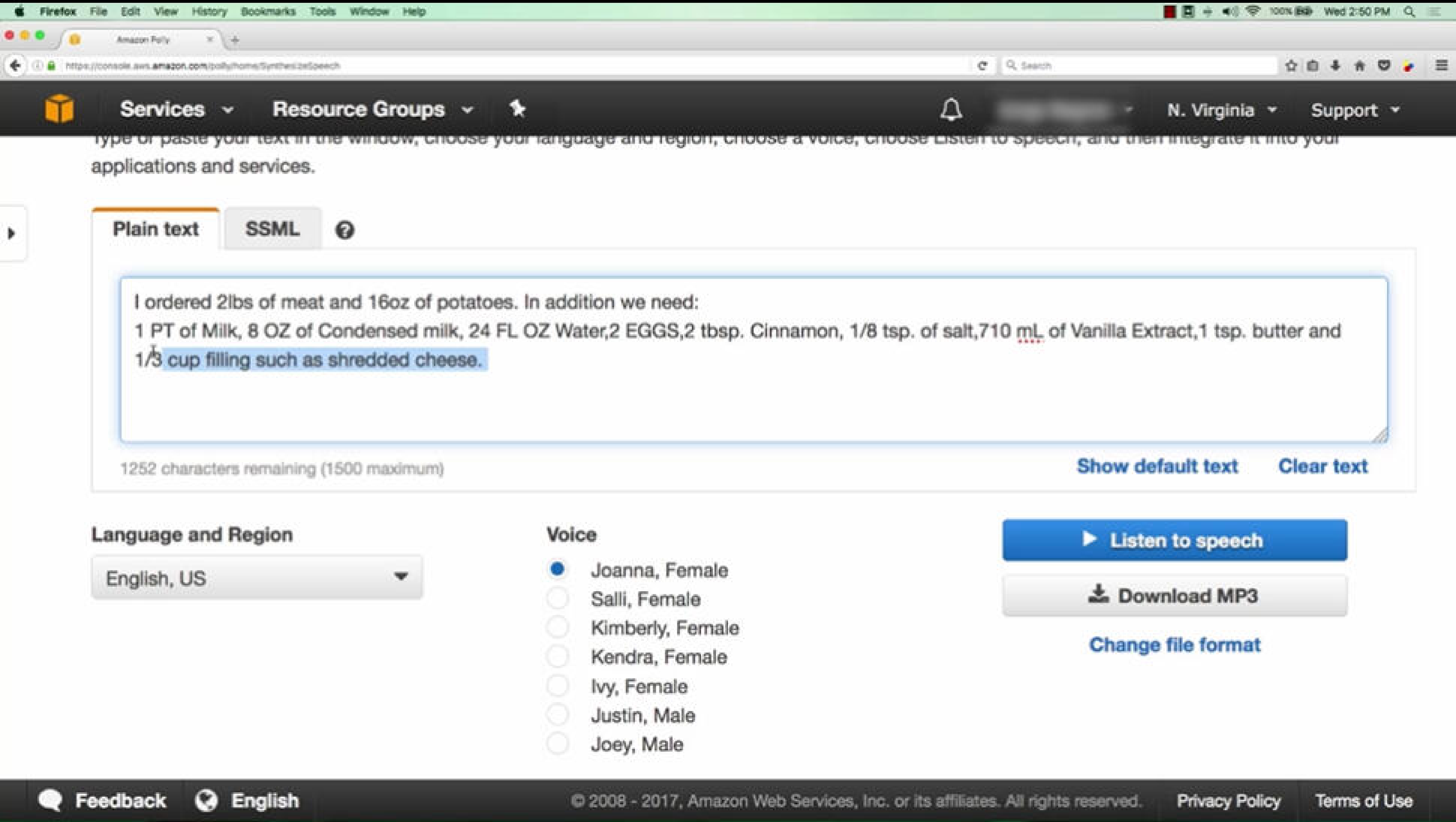
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Resource Groups
N. Virginia
Support
applications and services.
Plain text
SSML
I ordered 2lbs of meat and 16oz of potatoes. In addition we need:
1 PT of Milk, 8 OZ of Condensed milk, 24 FL OZ Water,2 EGGS,2 tbsp. Cinnamon, 1/8 tsp. of salt,710 mL of Vanilla Extract,1 tsp. butter and 1/3 cup filling such as shredded cheese.
1252 characters remaining (1500 maximum)
Show default text
Clear text
Language and Region
English, US
Voice
Joanna, Female
Salli, Female
Kimberly, Female
Kendra, Female
Ivy, Female
Justin, Male
Joey, Male
Listen to speech
Download MP3
Change file format
Feedback
English
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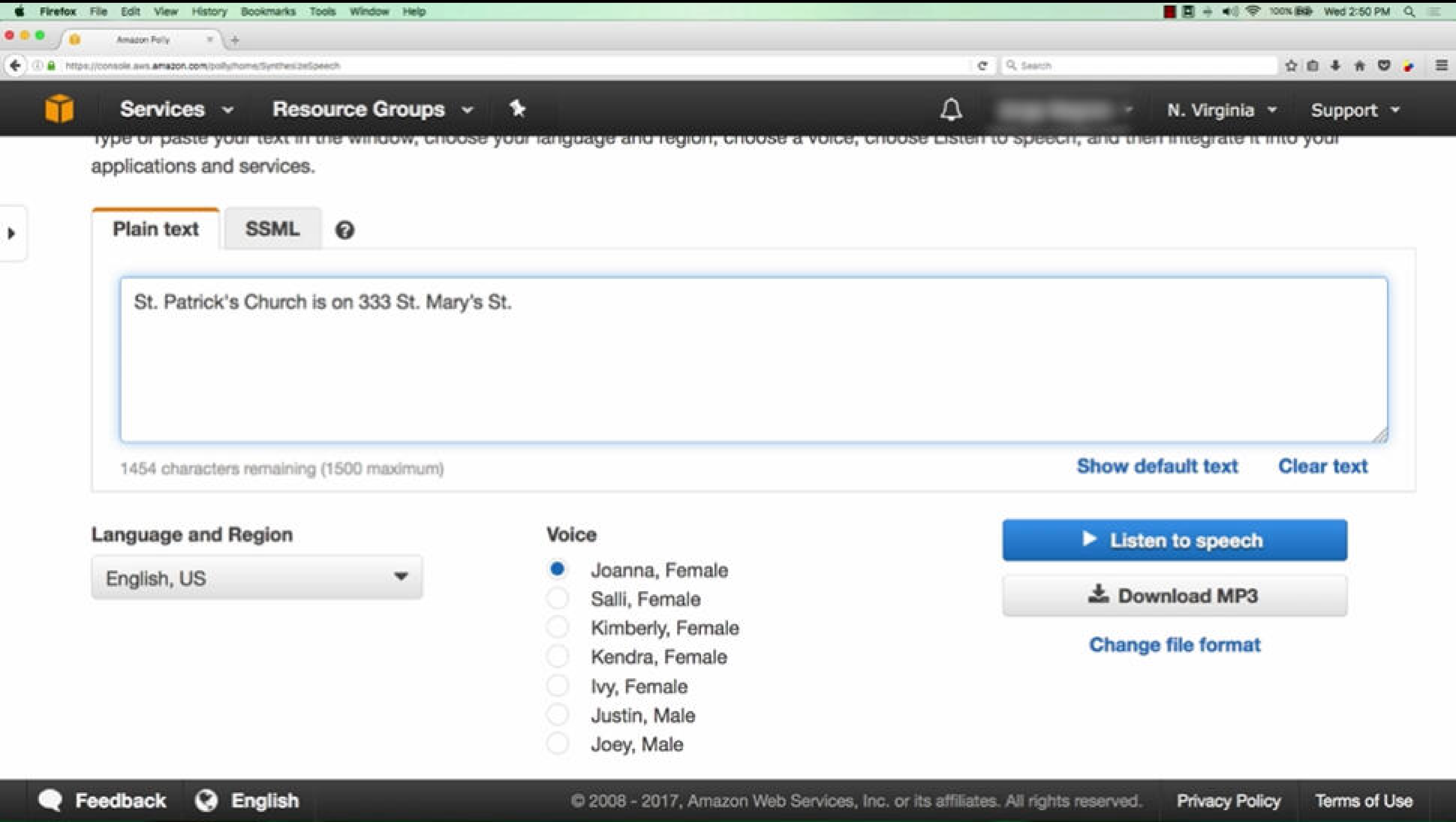
Services
Resource Groups
N. Virginia
Support
applications and services.
Plain text
SSML
St. Patrick's Church is on 333 St. Mary's St.
1454 characters remaining (1500 maximum)
Show default text
Clear text
Language and Region
English, US
Voice
Joanna, Female
Salli, Female
Kimberly, Female
Kendra, Female
Ivy, Female
Justin, Male
Joey, Male
Listen to speech
Download MP3
Change file format
Feedback
English
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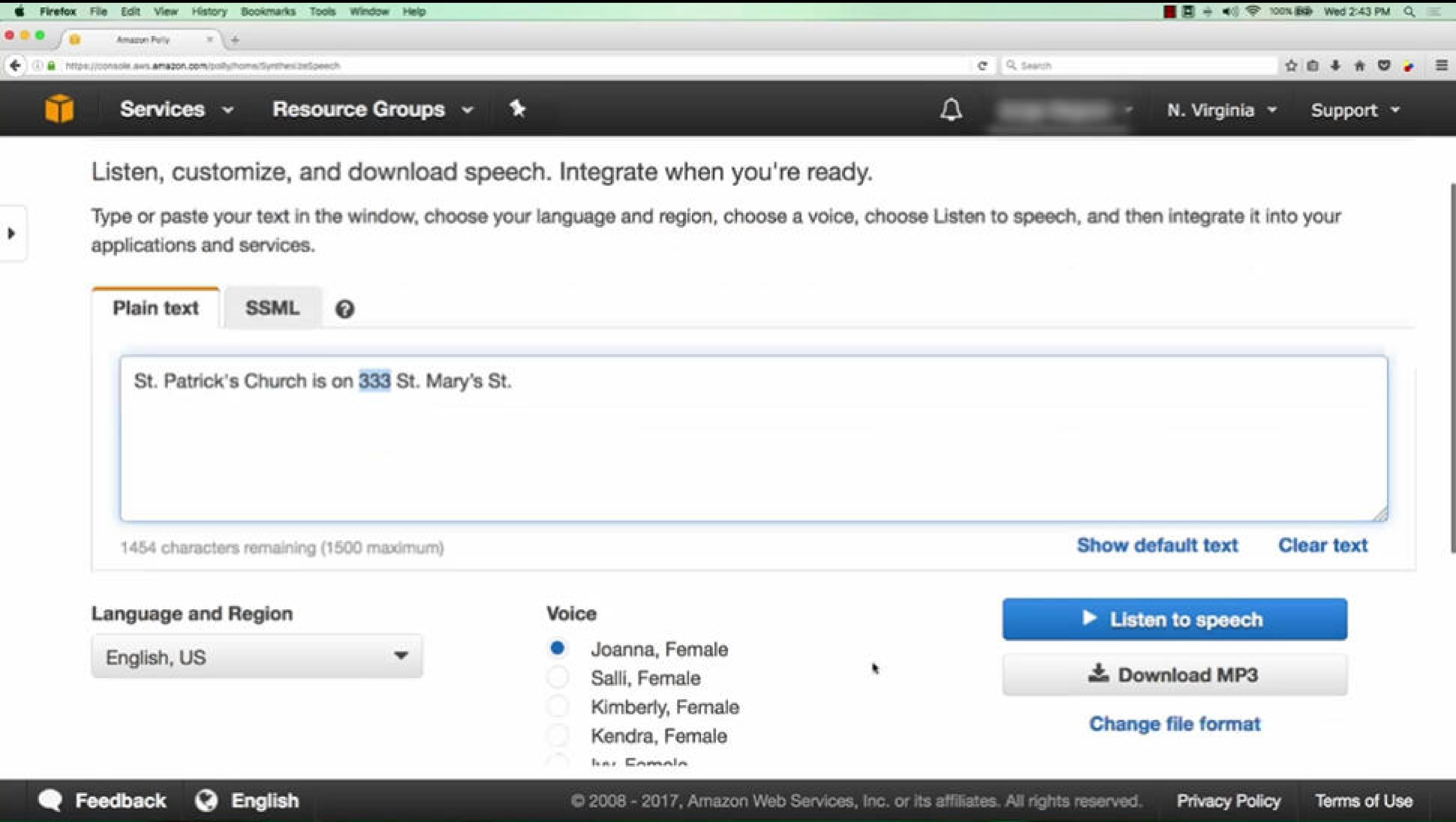
Firefox File Edit View History Bookmarks Tools Window Help
Wed 2:43 PM
Amazon Polly
Search
Services
Resource Groups
N. Virginia
Support
Listen, customize, and download speech. Integrate when you're ready.
Type or paste your text in the window, choose your language and region, choose a voice, choose Listen to speech, and then integrate it into your applications and services.
Plain text
SSML
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1454 characters remaining (1500 maximum)
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Language and Region
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Listen to speech
Download MP3
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Feedback
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Amazon Polly

https://console.aws.amazon.com/polly/home/SynthesizeSpeech

Services Resource Groups [redacted] N. Virginia Support

Type or paste your text in the window, choose your language and region, choose a voice, choose Listen to speech, and then integrate it into your applications and services.

Plain text | SSML

St. Patrick's Church is on 333 St. Mary's St.

1454 characters remaining (1500 maximum)

Show default text Clear text

Language and Region

English, US

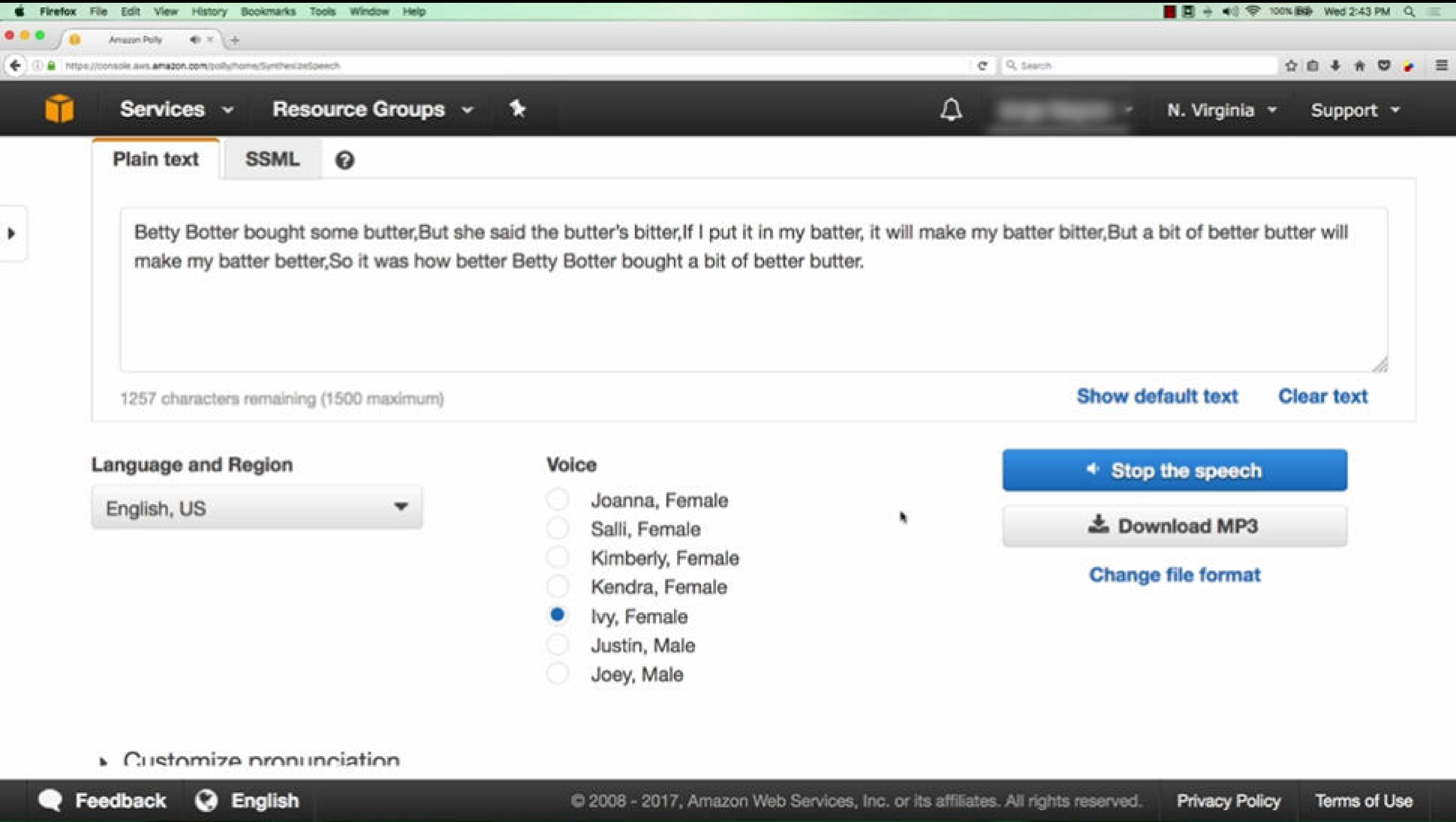
Voice

- Joanna, Female
- Salli, Female
- Kimberly, Female
- Kendra, Female
- Ivy, Female
- Justin, Male

Listen to speech

Download MP3

Change file format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Wed 2:43 PM
Amazon Polly
https://console.aws.amazon.com/polly/home/SynthesizeSpeech
Search
Services
Resource Groups
N. Virginia
Support
Plain text
SSML
Betty Botter bought some butter,But she said the butter's bitter,If I put it in my batter, it will make my batter bitter,But a bit of better butter will make my batter better,So it was how better Betty Botter bought a bit of better butter.
1257 characters remaining (1500 maximum)
Show default text
Clear text
Language and Region
English, US
Voice
Joanna, Female
Salli, Female
Kimberly, Female
Kendra, Female
Ivy, Female
Justin, Male
Joey, Male
Stop the speech
Download MP3
Change file format
Customize pronunciation
Feedback
English
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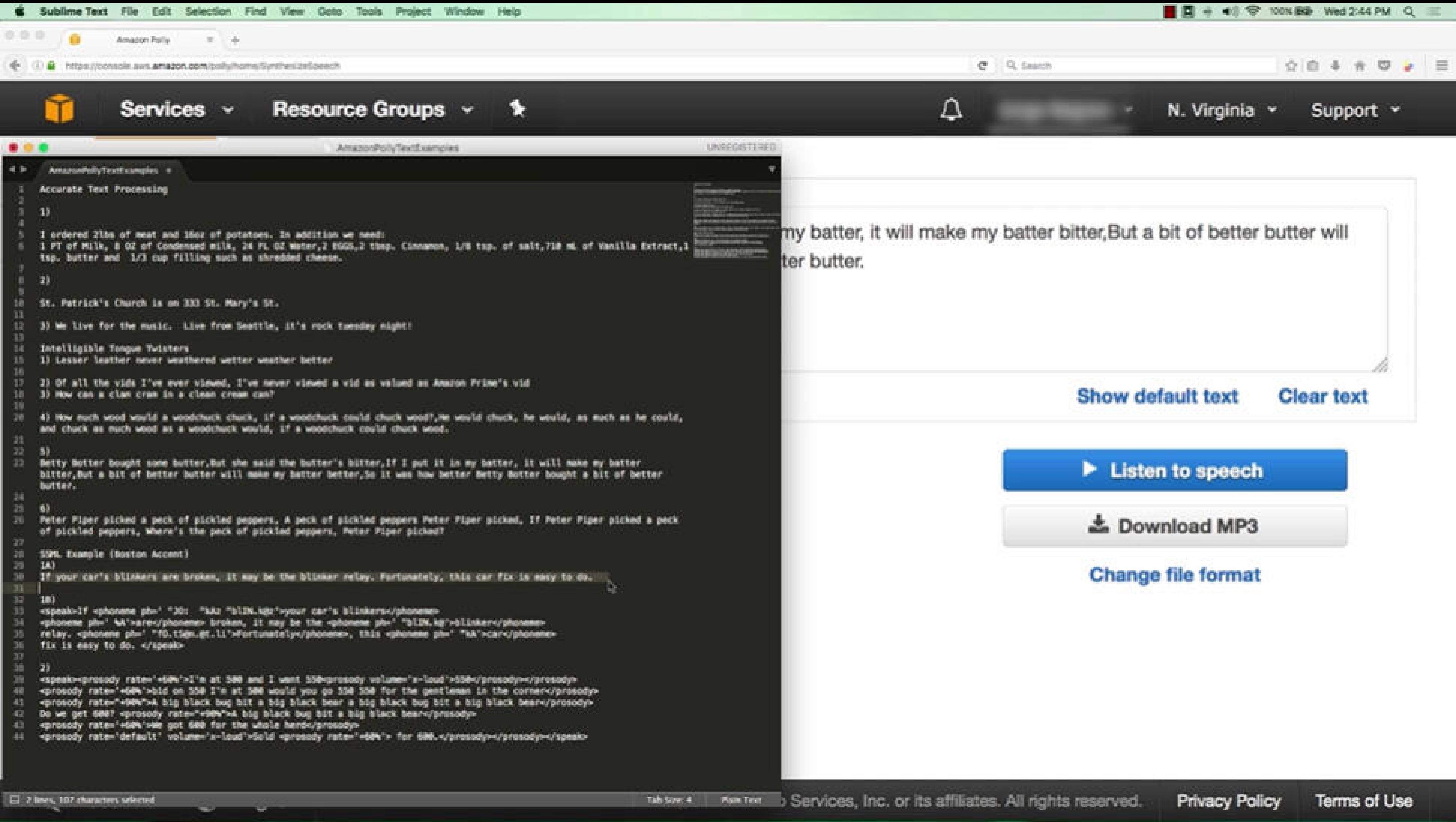
Sublime Text File Edit Selection Find View Goto Tools Project Window Help
Wed 2:44 PM
Amazon Polly
Services
Resource Groups
N. Virginia
Support
AmazonPollyTextExamples
UNREGISTERED
Accurate Text Processing
1)
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1) Lesser leather never weathered wetter weather better
2) Of all the vids I've ever viewed, I've never viewed a vid as valued as Amazon Prime's vid
3) How can a clam cram in a clean cream can?
4) How much wood would a woodchuck chuck, if a woodchuck could chuck wood?,He would chuck, he would, as much as he could, and chuck as much wood as a woodchuck would, if a woodchuck could chuck wood.
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6)
Peter Piper picked a peck of pickled peppers, A peck of pickled peppers Peter Piper picked, If Peter Piper picked a peck of pickled peppers, Where's the peck of pickled peppers, Peter Piper picked?
SSML Example (Boston Accent)
1A)
If your car's blinkers are broken, it may be the blinker relay. Fortunately, this car fix is easy to do.
1B)
fix is easy to do. </speak>
2)
<prosody rate='default' volume='x-loud'>Sold <prosody rate='+60%'> for 600.</prosody></prosody></speak>
2 lines, 107 characters selected
Tab Size: 4
Plain Text
my batter, it will make my batter bitter,But a bit of better butter will
tter butter.
Show default text
Clear text
Listen to speech
Download MP3
Change file format
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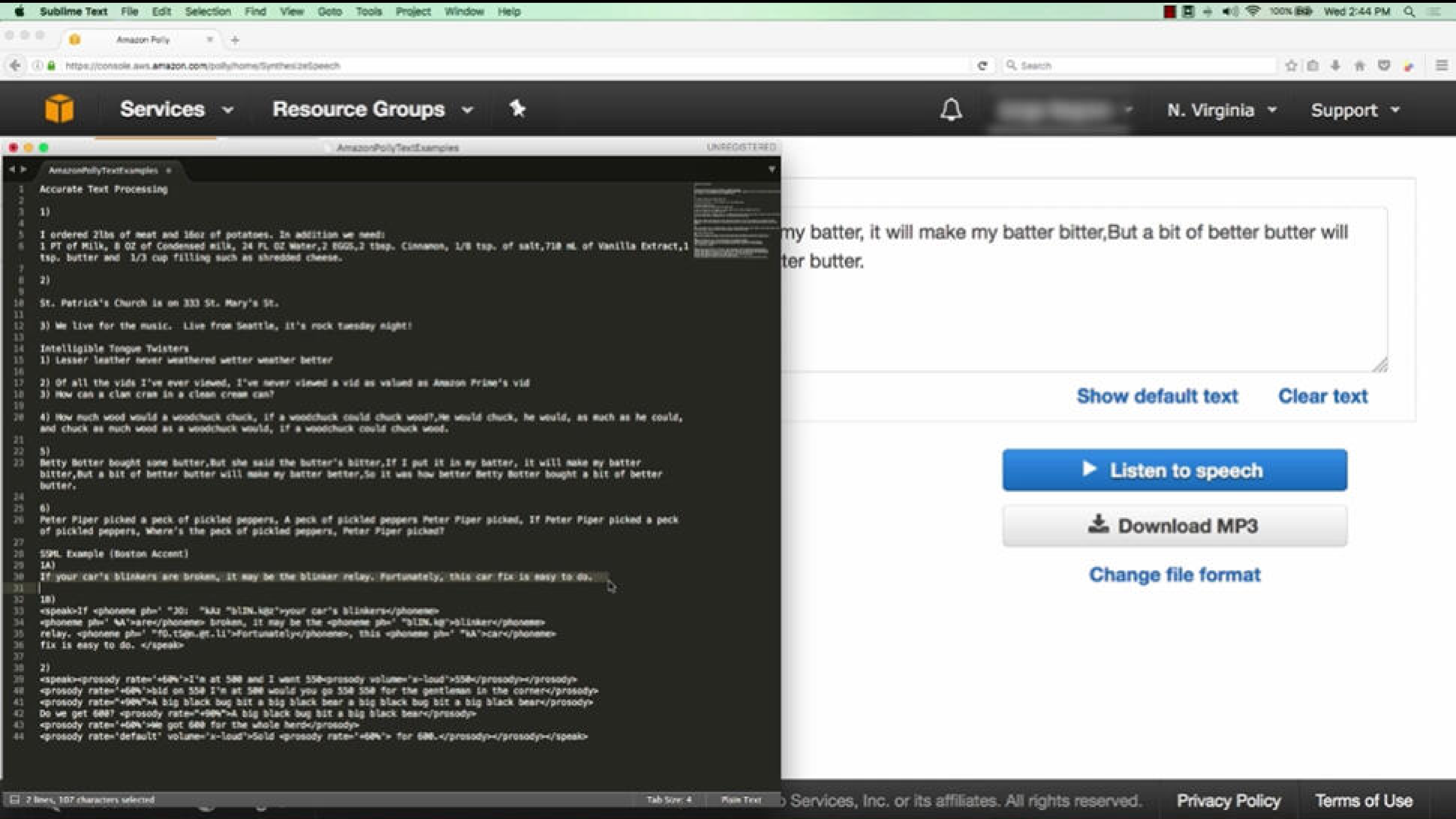

Sublime Text File Edit Selection Find View Goto Tools Project Window Help
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Amazon Polly
https://console.aws.amazon.com/polly/home/SynthesizeSpeech
Services
Resource Groups
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AmazonPollyTextExamples
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Accurate Text Processing
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6)
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1B)
<speak>If <phoneme ph='...'>your car's blinkers</phoneme>
<phoneme ph='...'>are</phoneme> broken, it may be the <phoneme ph='...'>blinker</phoneme>
relay. <phoneme ph='...'>Fortunately</phoneme>, this <phoneme ph='...'>car</phoneme>
fix is easy to do. </speak>
2)
<speak><prosody rate='+60%'>I'm at 500 and I want 550<prosody volume='x-loud'>550</prosody></prosody>
<prosody rate='+60%'>bid on 550 I'm at 500 would you go 550 550 for the gentleman in the corner</prosody>
<prosody rate="+90%">A big black bug bit a big black bear a big black bug bit a big black bear</prosody>
Do we get 600? <prosody rate="+90%">A big black bug bit a big black bear</prosody>
<prosody rate='+60%'>We got 600 for the whole herd</prosody>
<prosody rate='default' volume='x-loud'>Sold <prosody rate='+60%'> for 600.</prosody></prosody></speak>
2 lines, 107 characters selected
Tab Size: 4
Plain Text
my batter, it will make my batter bitter,But a bit of better butter will
tter butter.
Show default text
Clear text
Listen to speech
Download MP3
Change file format
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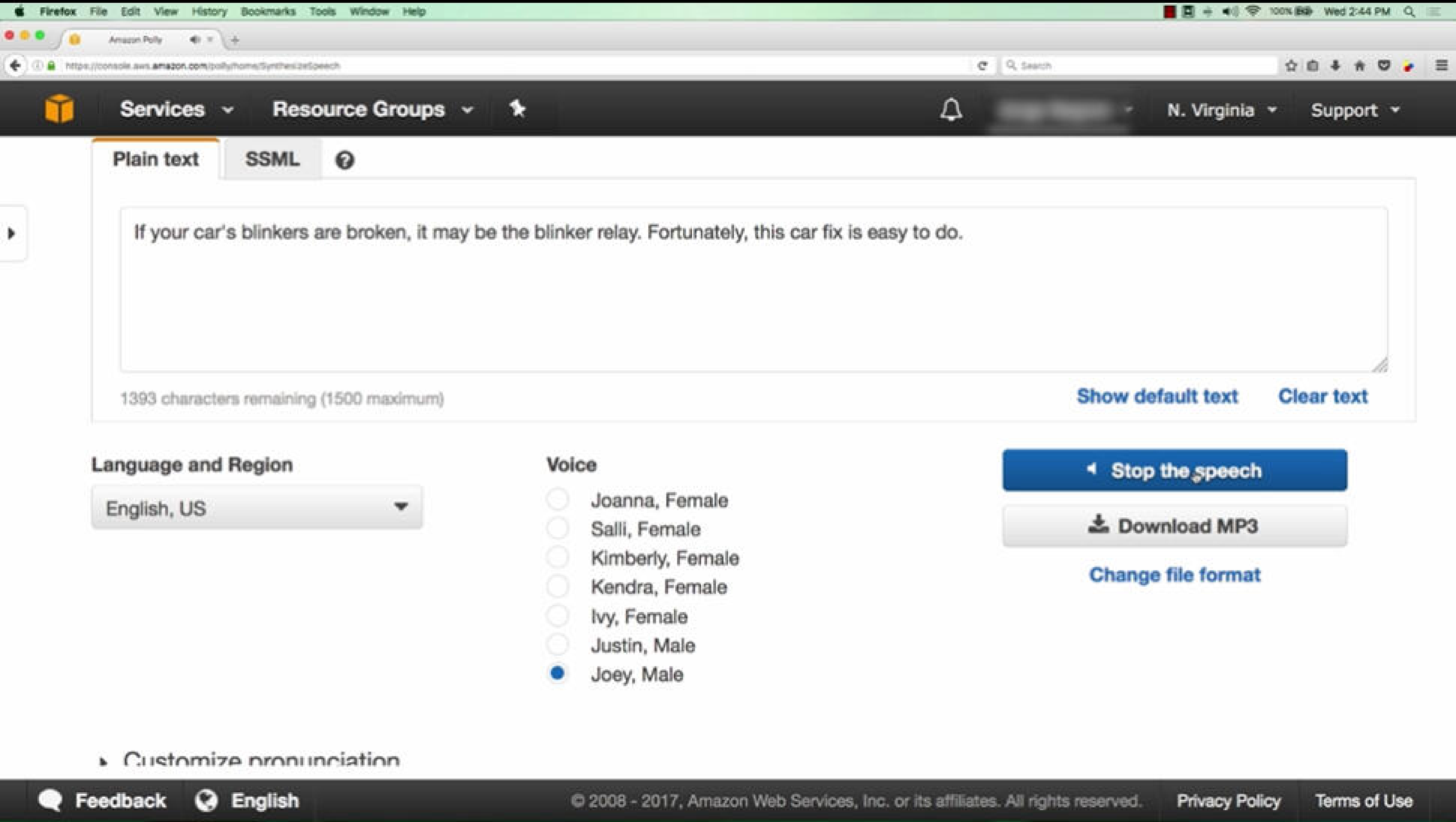
Firefox File Edit View History Bookmarks Tools Window Help
Wed 2:44 PM
Amazon Polly
https://console.aws.amazon.com/polly/home/SynthesizeSpeech
Services
Resource Groups
N. Virginia
Support
Plain text
SSML
If your car's blinkers are broken, it may be the blinker relay. Fortunately, this car fix is easy to do.
1393 characters remaining (1500 maximum)
Show default text
Clear text
Language and Region
English, US
Voice
Joanna, Female
Salli, Female
Kimberly, Female
Kendra, Female
Ivy, Female
Justin, Male
Joey, Male
Stop the speech
Download MP3
Change file format
Customize pronunciation
Feedback
English
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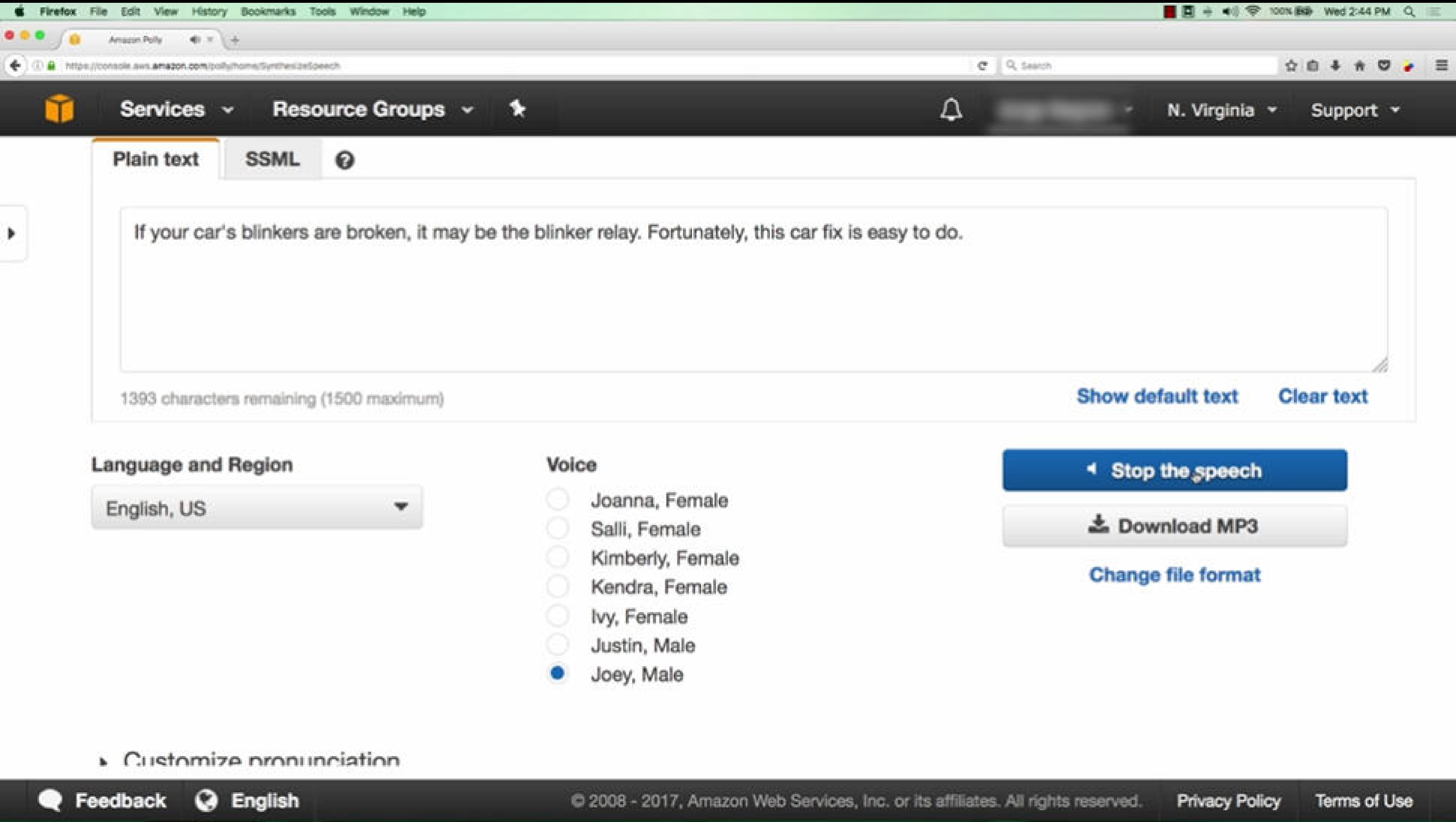

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Wed 2:44 PM
Amazon Polly
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Services
Resource Groups
N. Virginia
Support
Plain text
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Language and Region
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Voice
Joanna, Female
Salli, Female
Kimberly, Female
Kendra, Female
Ivy, Female
Justin, Male
Joey, Male
Stop the speech
Download MP3
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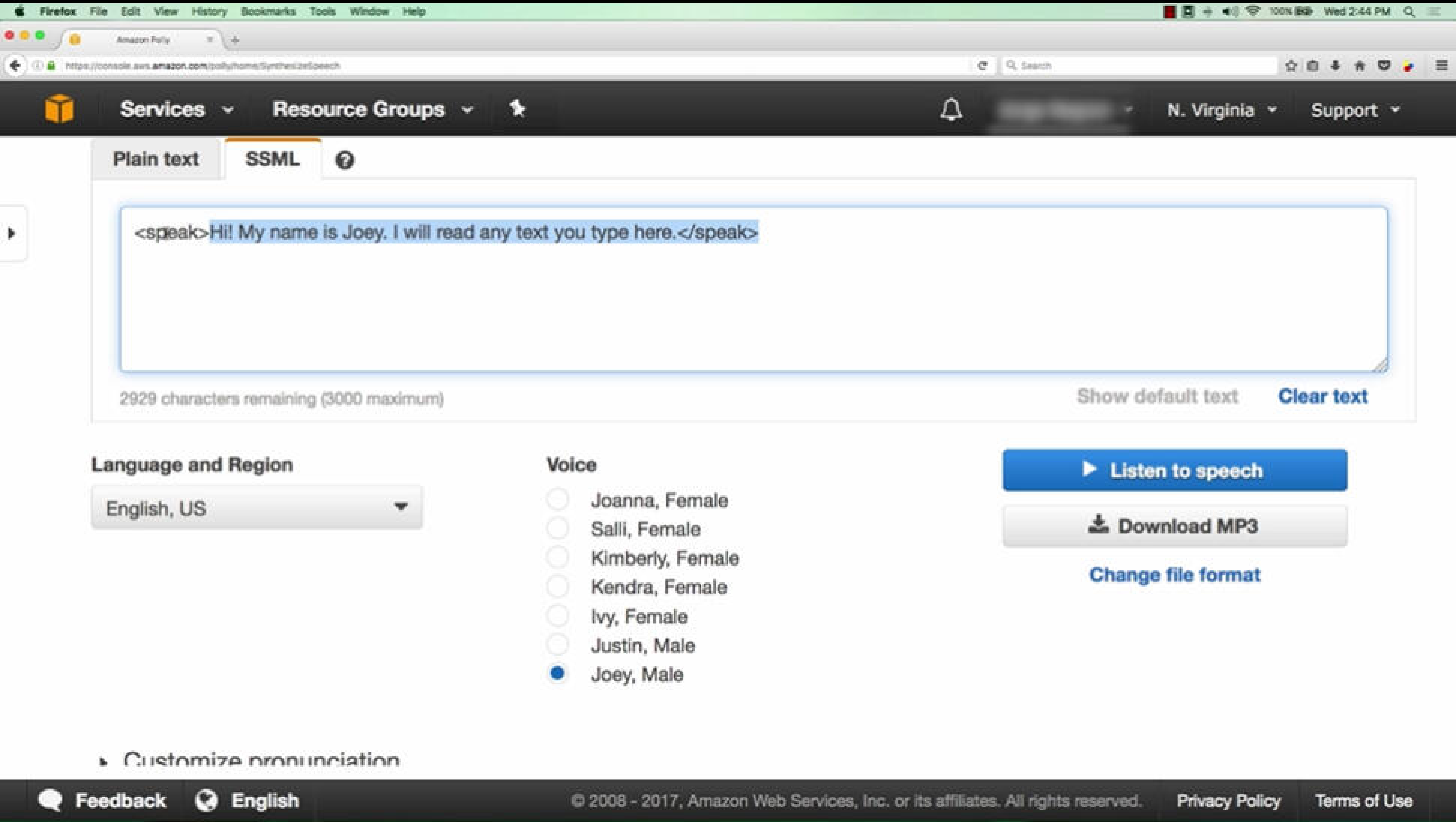
Firefox File Edit View History Bookmarks Tools Window Help
Wed 2:44 PM
Amazon Polly
Search
Services
Resource Groups
N. Virginia
Support
Plain text
SSML
<speak>Hi! My name is Joey. I will read any text you type here.</speak>
2929 characters remaining (3000 maximum)
Show default text
Clear text
Language and Region
English, US
Voice
Joanna, Female
Salli, Female
Kimberly, Female
Kendra, Female
Ivy, Female
Justin, Male
Joey, Male
Listen to speech
Download MP3
Change file format
Customize pronunciation
Feedback
English
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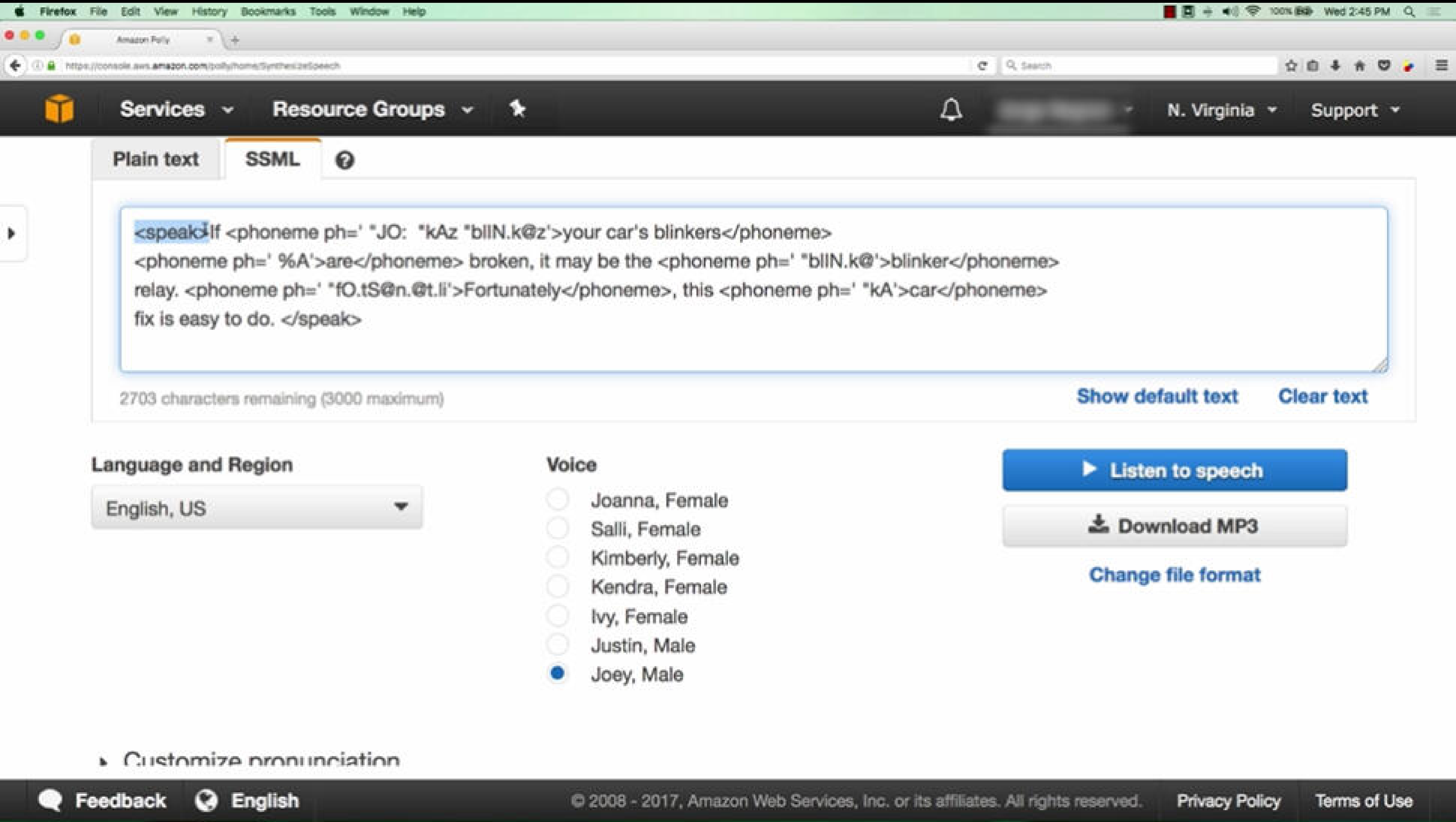
Firefox File Edit View History Bookmarks Tools Window Help
Wed 2:45 PM
Amazon Polly
https://console.aws.amazon.com/polly/home/SynthesizeSpeech
Services
Resource Groups
N. Virginia
Support
Plain text
SSML
<speak>If <phoneme ph=' "JO: "kAz "blIN.k@z'>your car's blinkers</phoneme>
<phoneme ph=' %A'>are</phoneme> broken, it may be the <phoneme ph=' "blIN.k@'>blinker</phoneme>
relay. <phoneme ph=' "fO.tS@n.@t.li'>Fortunately</phoneme>, this <phoneme ph=' "kA'>car</phoneme>
fix is easy to do. </speak>
2703 characters remaining (3000 maximum)
Show default text
Clear text
Language and Region
English, US
Voice
Joanna, Female
Salli, Female
Kimberly, Female
Kendra, Female
Ivy, Female
Justin, Male
Joey, Male
Listen to speech
Download MP3
Change file format
Customize pronunciation
Feedback
English
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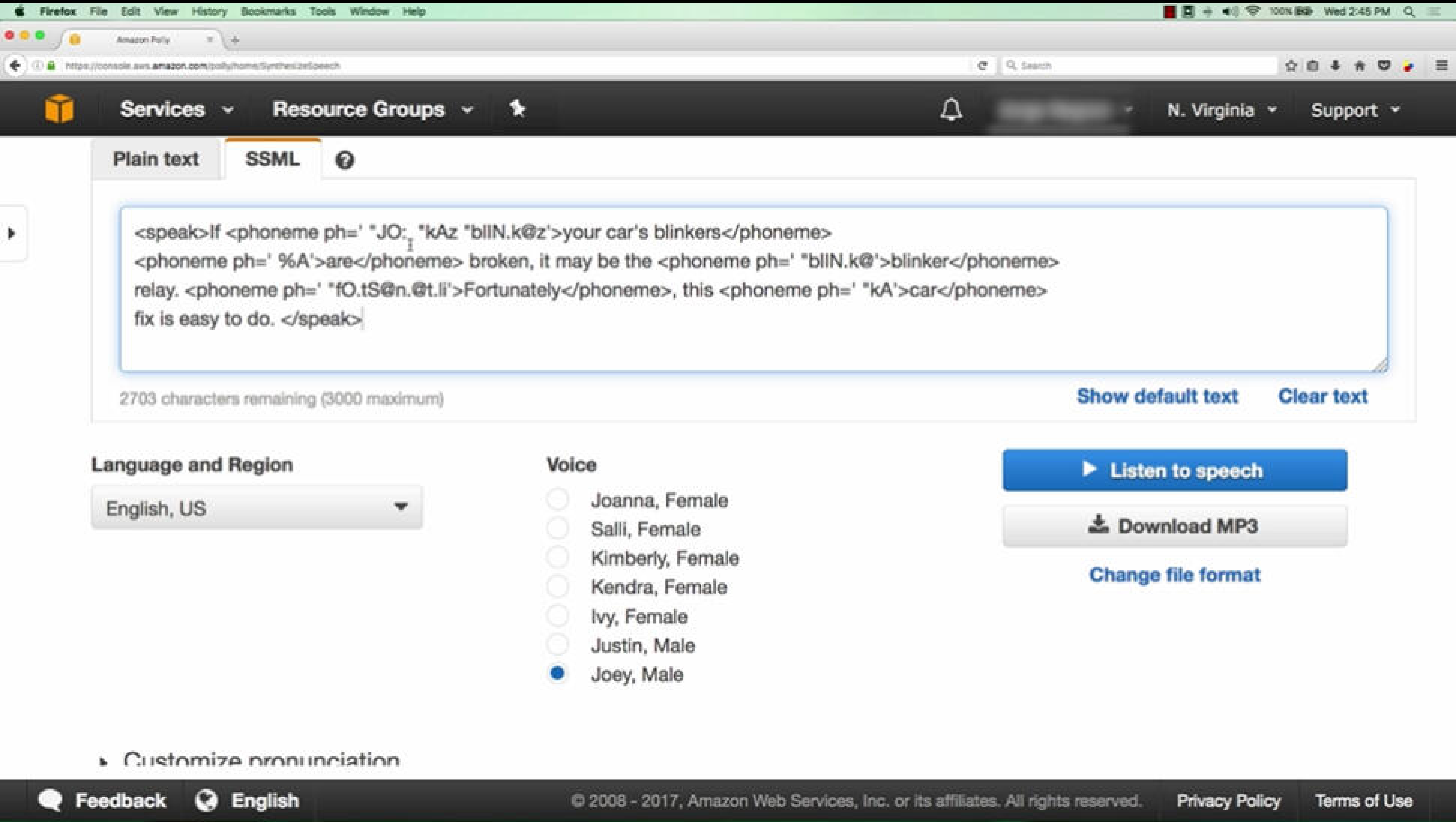
Services
Resource Groups
N. Virginia
Support
Plain text
SSML
<speak>If <phoneme ph=' "JO:, "kAz "blIN.k@z'>your car's blinkers</phoneme>
<phoneme ph=' %A'>are</phoneme> broken, it may be the <phoneme ph=' "blIN.k@'>blinker</phoneme>
relay. <phoneme ph=' "fO.tS@n.@t.li'>Fortunately</phoneme>, this <phoneme ph=' "kA'>car</phoneme>
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2703 characters remaining (3000 maximum)
Show default text
Clear text
Language and Region
English, US
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Joanna, Female
Salli, Female
Kimberly, Female
Kendra, Female
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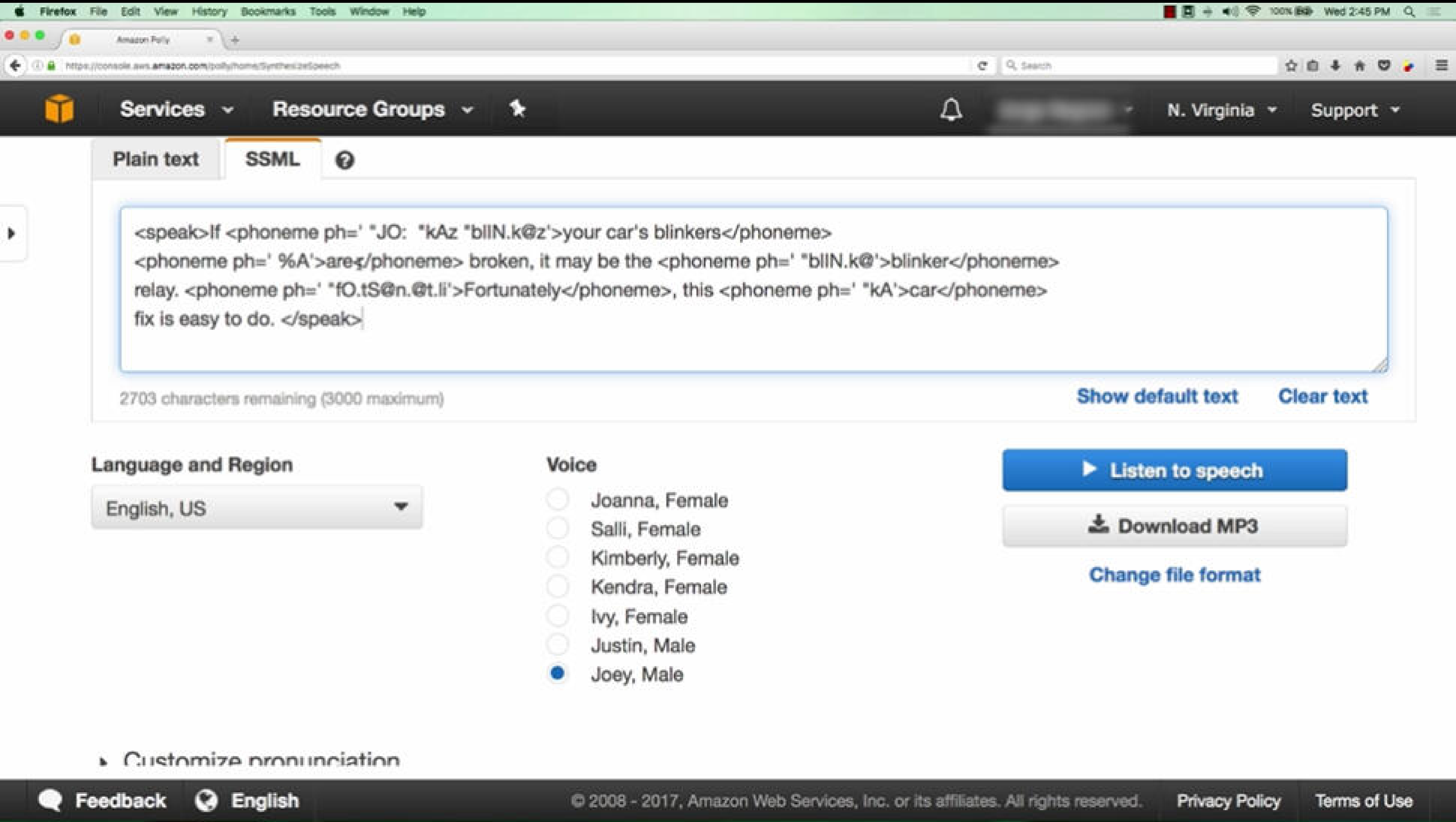
Firefox File Edit View History Bookmarks Tools Window Help
Wed 2:45 PM
Amazon Polly
Services
Resource Groups
N. Virginia
Support
Plain text
SSML
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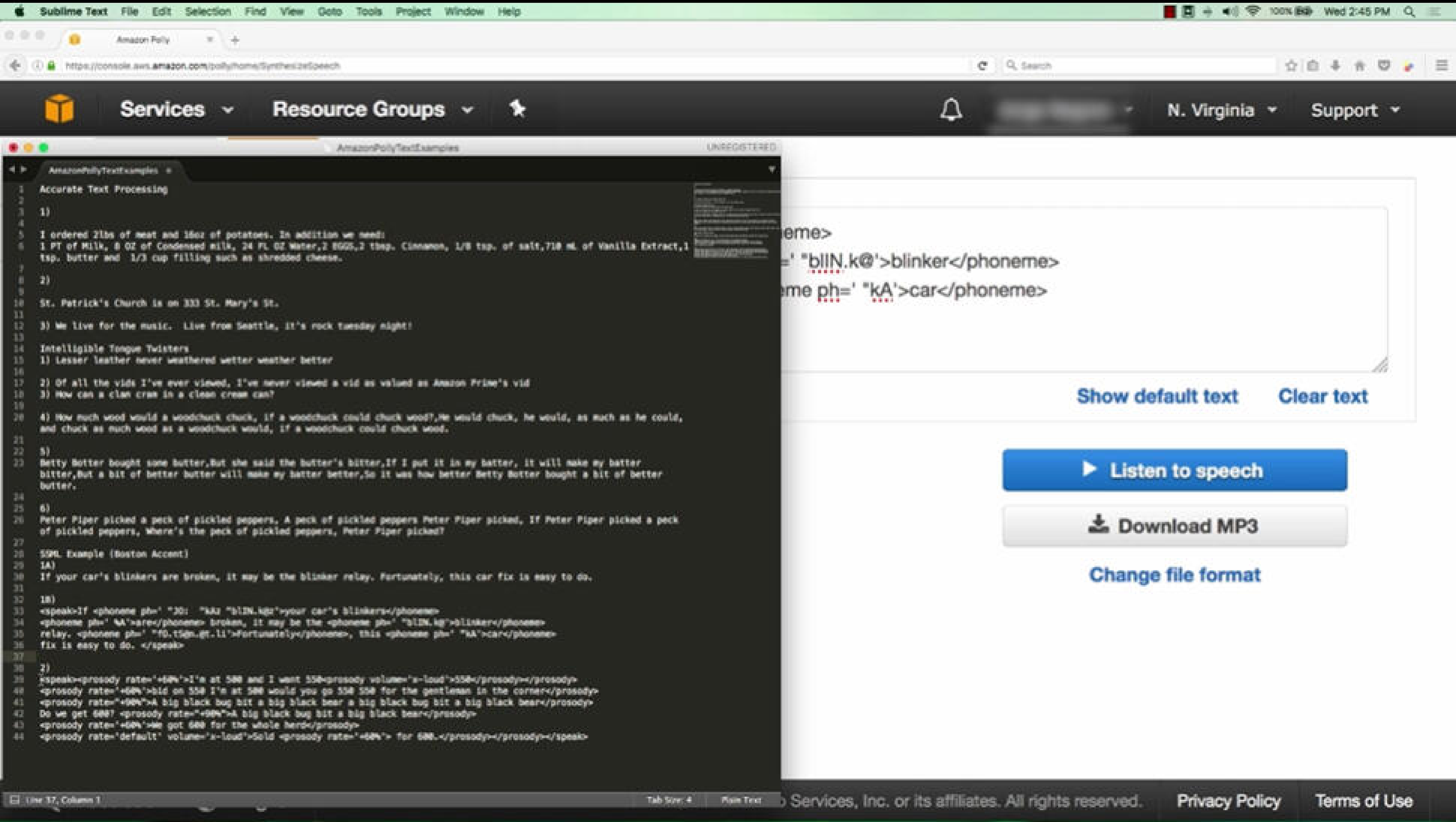
Sublime Text File Edit Selection Find View Goto Tools Project Window Help
Wed 2:45 PM
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Search
Services
Resource Groups
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Support
AmazonPollyTextExamples
UNREGISTERED
Accurate Text Processing
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<prosody rate='+60%'>bid on 550 I'm at 500 would you go 550 550 for the gentleman in the corner</prosody>
<prosody rate="+90%">A big black bug bit a big black bear a big black bug bit a big black bear</prosody>
Do we get 600? <prosody rate="+90%">A big black bug bit a big black bear</prosody>
<prosody rate='+60%'>We got 600 for the whole herd</prosody>
<prosody rate='default' volume='x-loud'>Sold <prosody rate='+60%'> for 600.</prosody></prosody></speak>
Line 37, Column 1
Tab Size: 4
Plain Text
eme>
=' "blIN.k@'>blinker</phoneme>
eme ph=' "kA'>car</phoneme>
Show default text
Clear text
Listen to speech
Download MP3
Change file format
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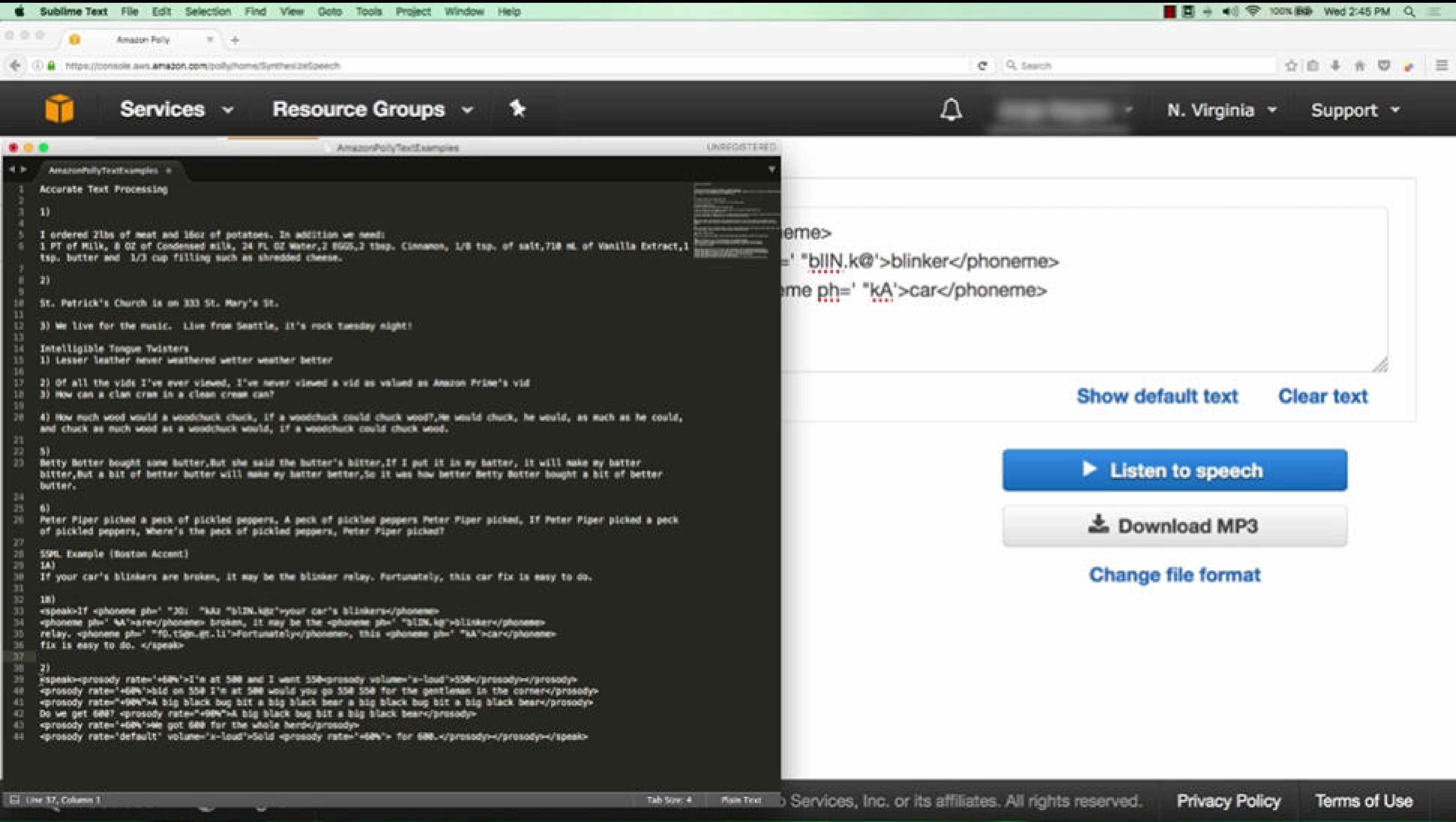
Sublime Text File Edit Selection Find View Goto Tools Project Window Help
Wed 2:45 PM
Amazon Polly
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me ph=' "kA'>car</phoneme>
Show default text
Clear text
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Download MP3
Change file format
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Line 37, Column 1
Tab Size: 4
Plain Text

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Amazon Polly

https://console.aws.amazon.com/polly/home/SynthesizeSpeech

Services Resource Groups N. Virginia Support

Text-to-Speech

Listen, customize, and download speech. Integrate when you're ready.

Type or paste your text in the window, choose your language and region, choose a voice, choose Listen to speech, and then integrate it into your applications and services.

Plain text **SSML**

```
<prosody rate='+60%'>bid on 550 I'm at 500 would you go 550 550 for the gentleman in the corner</prosody>
<prosody rate="+90%">A big black bug bit a big black bear a big black bug bit a big black bear</prosody>
Do we get 600? <prosody rate="+90%">A big black bug bit a big black bear</prosody>
<prosody rate='+60%'>We got 600 for the whole herd</prosody>
<prosody rate='default' volume='x-loud'>Sold <prosody rate='+60%'> for 600.</prosody></prosody></speak>
```

2439 characters remaining (3000 maximum)

Show default text Clear text

Language and Region

English, US

Voice

Joanna, Female

Salli, Female

Listen to speech

Download MP3

Feedback English

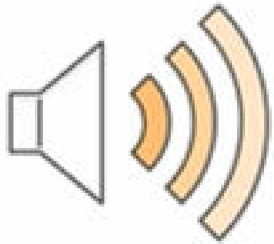
Privacy Policy Terms of Use

Thanks for watching!

aws training and certification

aws training and certification

What is Amazon Lex?

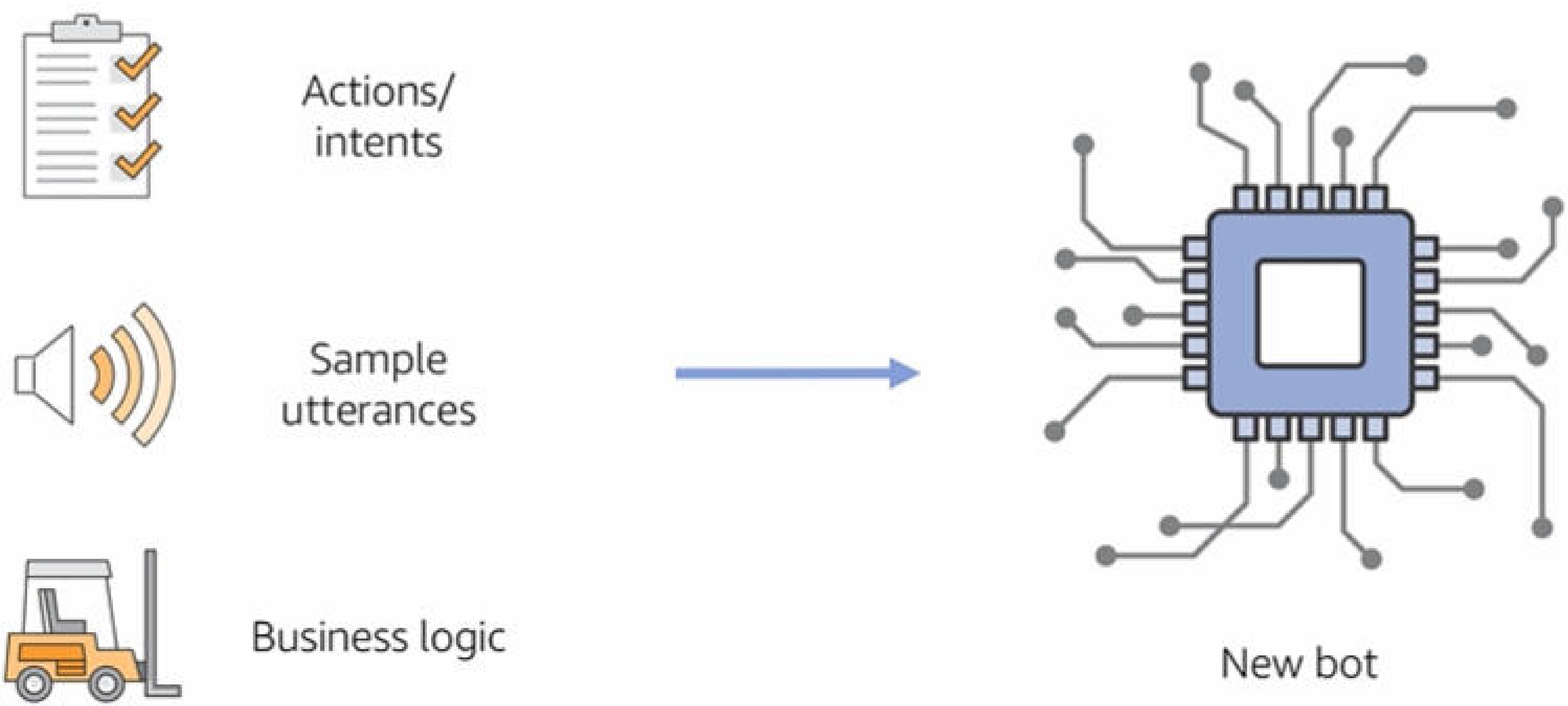


Conversational interfaces using voice and text

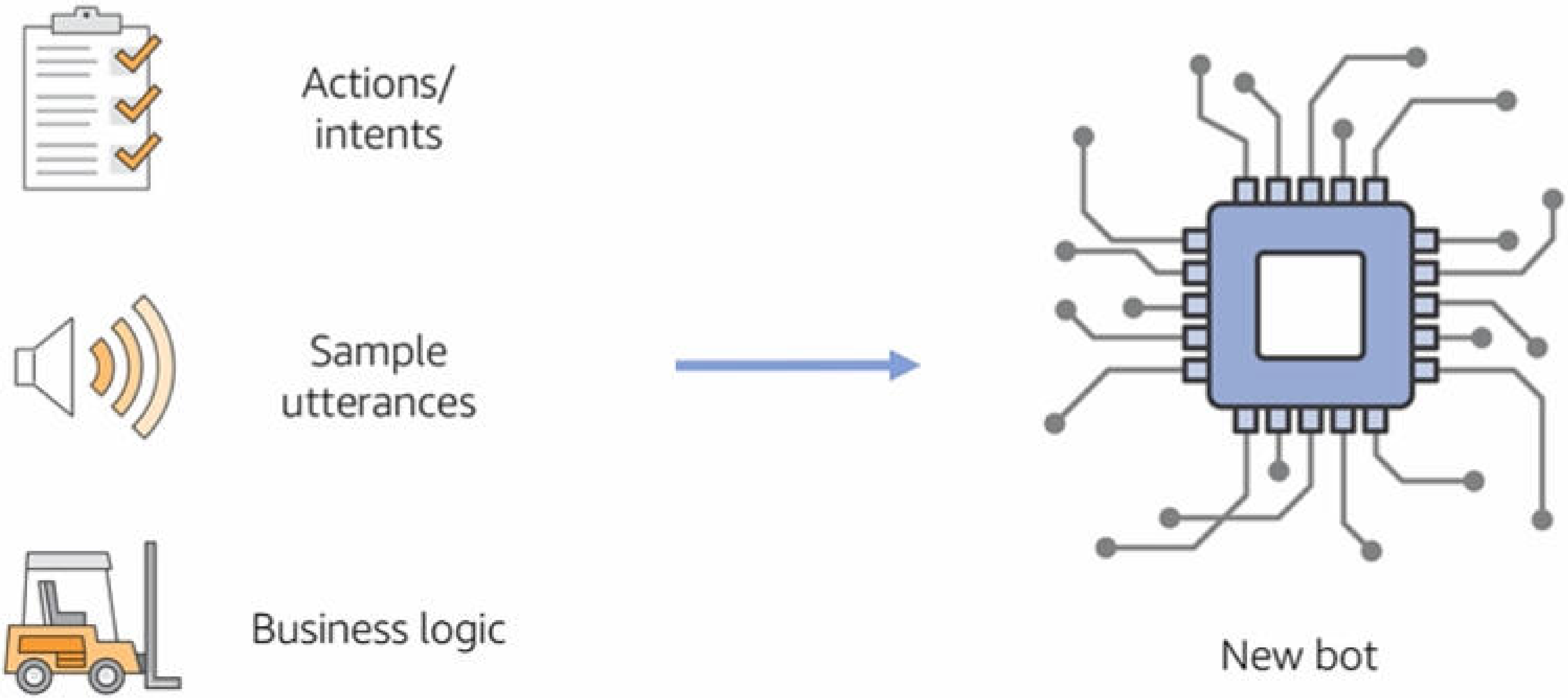
Automatic speech recognition (ASR) and Natural Language Understanding (NLU)

Build applications with highly engaging user experiences

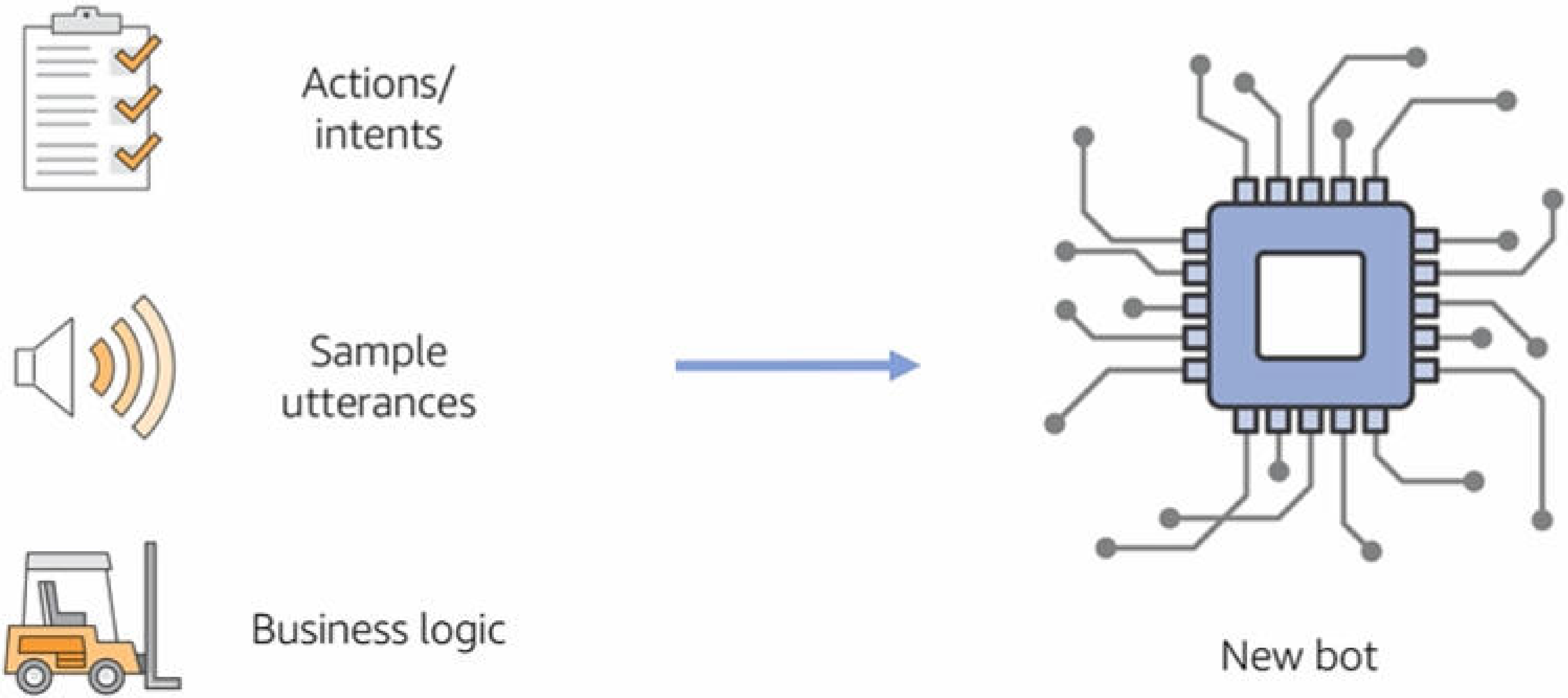
What Goes Into a Bot?



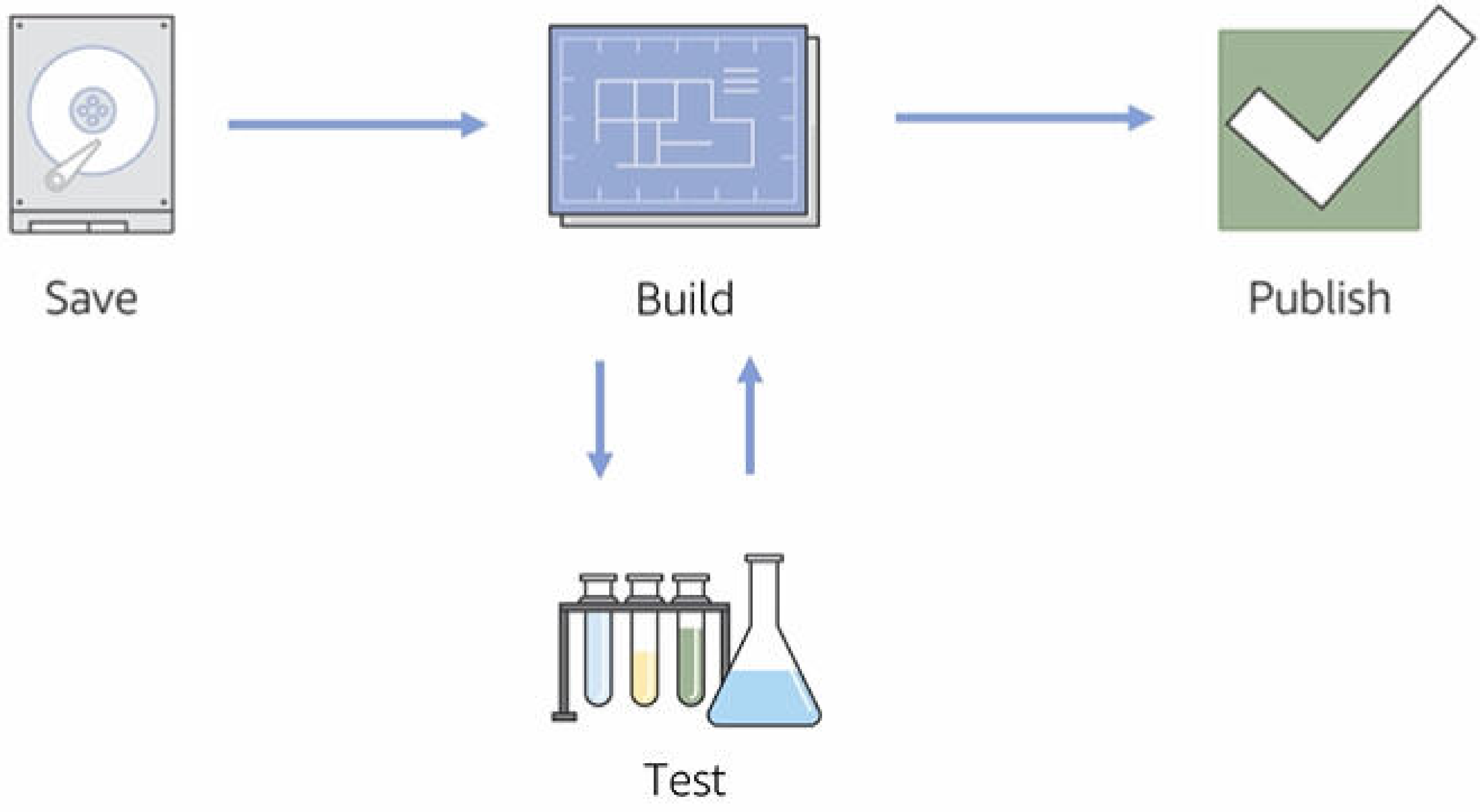
What Goes Into a Bot?



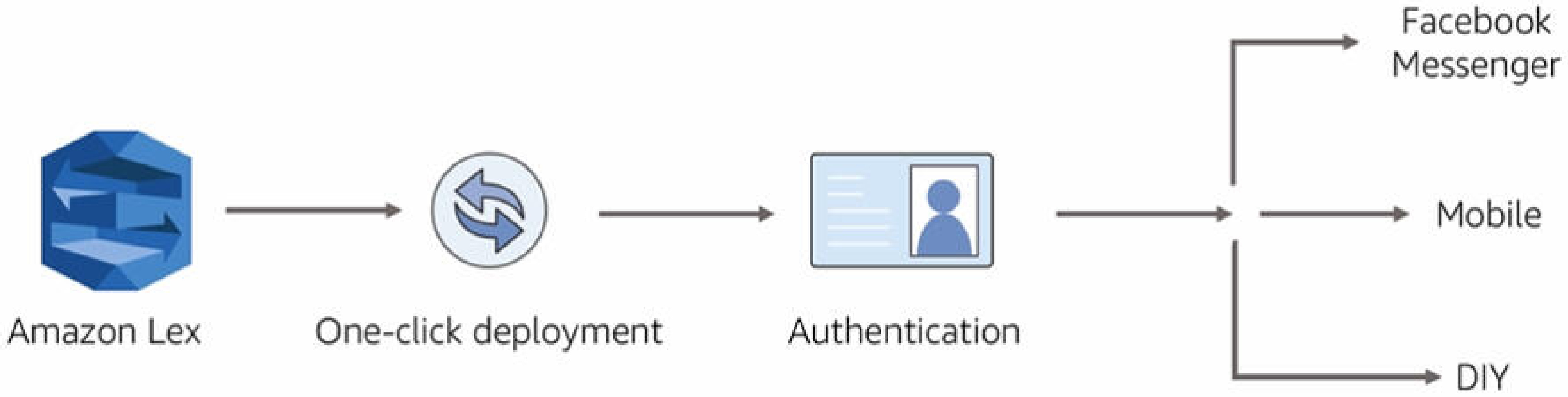
What Goes Into a Bot?



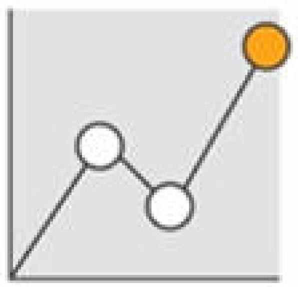
Amazon Lex Workflow



Deployment to Chat Services



Monitoring



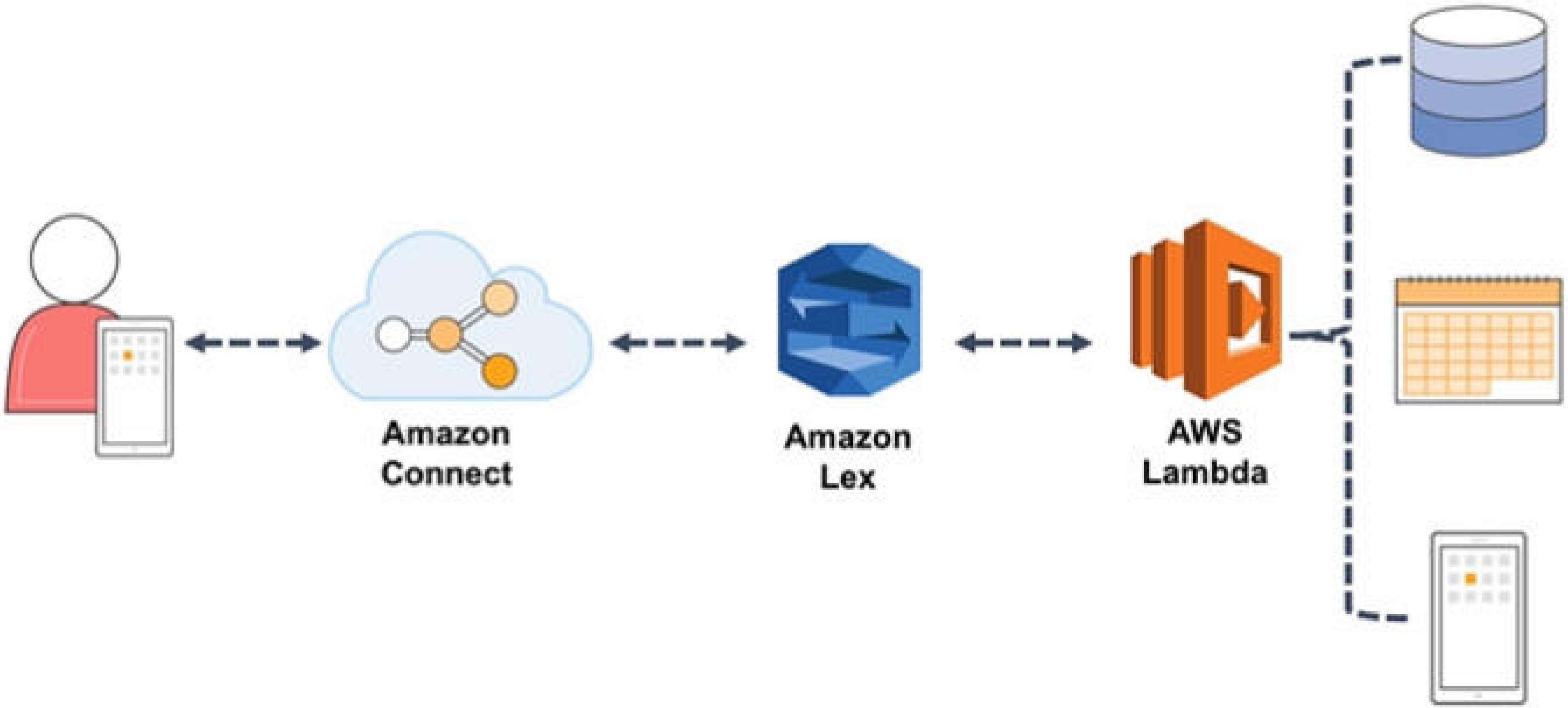
Number of requests

Latency

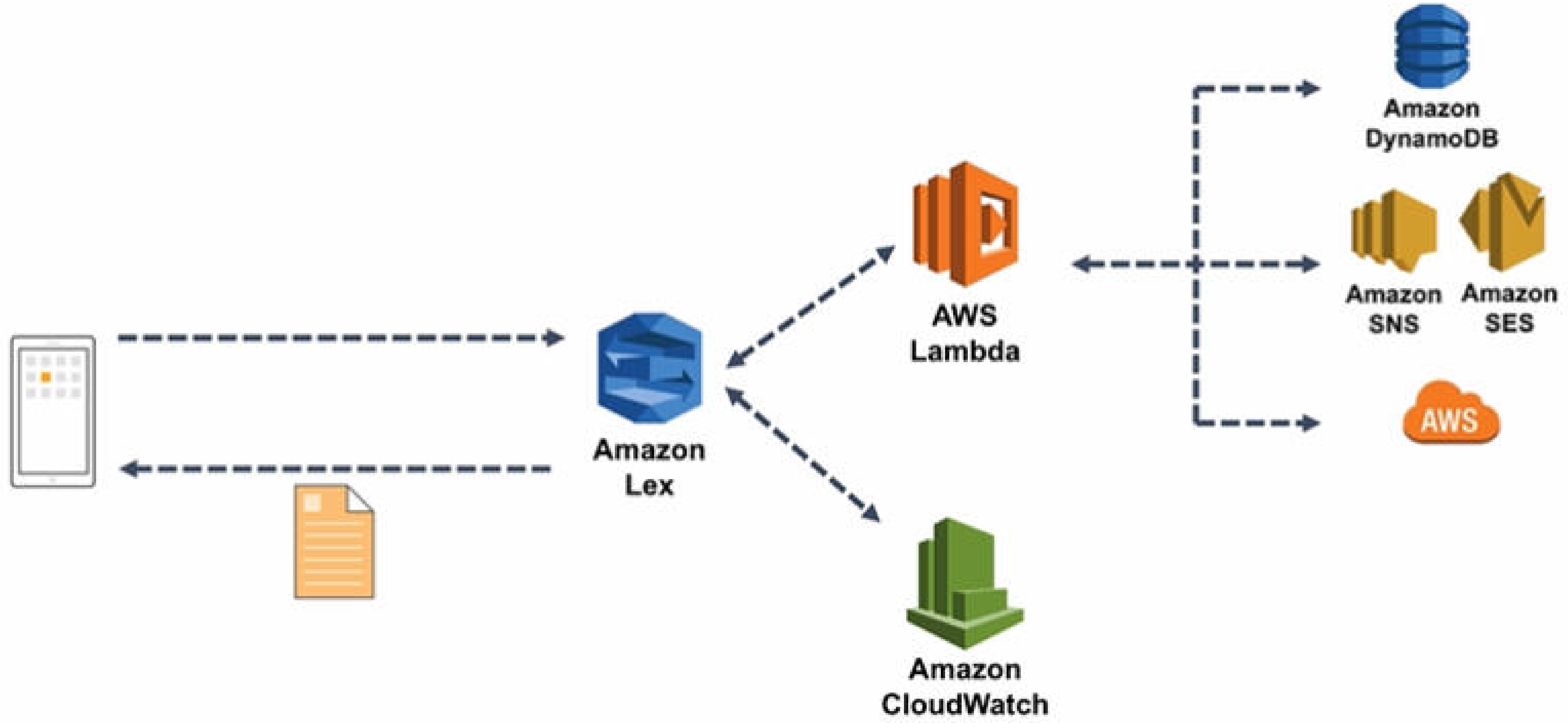
Errors

Use Cases

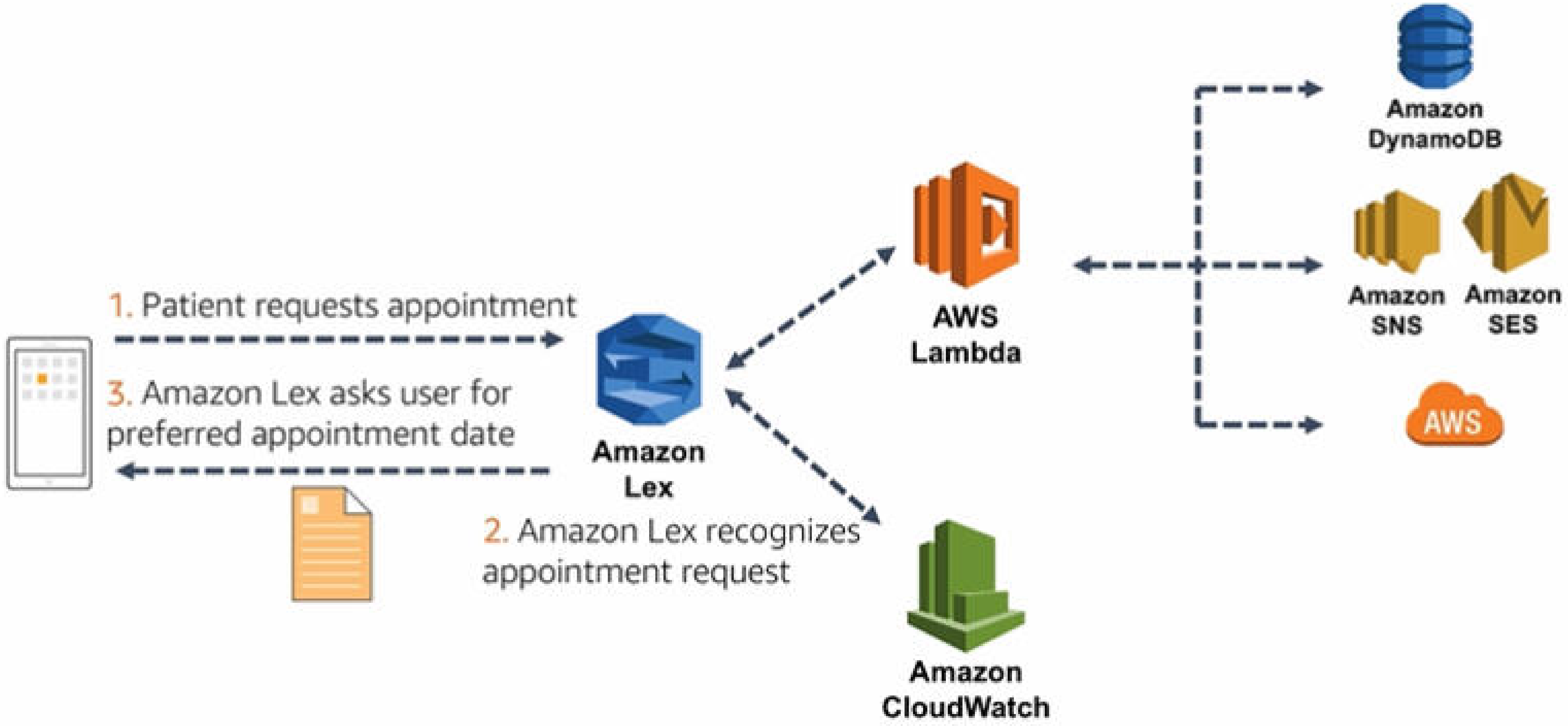
Use Case: Call Center Bots



Use Case: Informational Bots



Use Case: Informational Bots



Time-series forecasting

Science of predicting future points in a time series based on historical data.

Product demand

Workforce demand

Financial metrics

Inventory control

Forecasting accuracy

aws training and certification

- Historical data
- Holidays and vacations
- Economic indicators
- Weather conditions

The challenge:

aws training and certification

Traditional forecasting methods struggle with forecast accuracy.

- Spiky or intermittent data
- Additional variables
- External factors
- No history available

Introducing Amazon Forecast

aws training and certification

Amazon Forecast

- Fully-managed accuracy forecasting solution
- Uses deep learning models
- From over 10 years of machine learning experience
- Comes with multiple deep learning algorithms

Benefits

Accurate

Improves accuracy by up to 50 percent compared to traditional models

Benefits

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Improves accuracy by up to 50 percent compared to traditional models

Automated
Automates feature engineering, algorithm selection, and model tuning

Benefits

aws training and certification

Accurate
Improves accuracy by up to 50 percent compared to traditional models

Automated
Automates feature engineering, algorithm selection, and model tuning

Private and Secure
Creates a custom model for each customer without any data sharing

Customizable
Provides the ability to create your own algorithms or customize existing ones

How does it work?

Import data from Amazon S3 buckets

How does it work?

aws training and certification

Import data from Amazon S3 buckets

Manually or automatically select algorithms

Evaluate accuracy metrics and deploy to production

How does it work?

aws training and certification

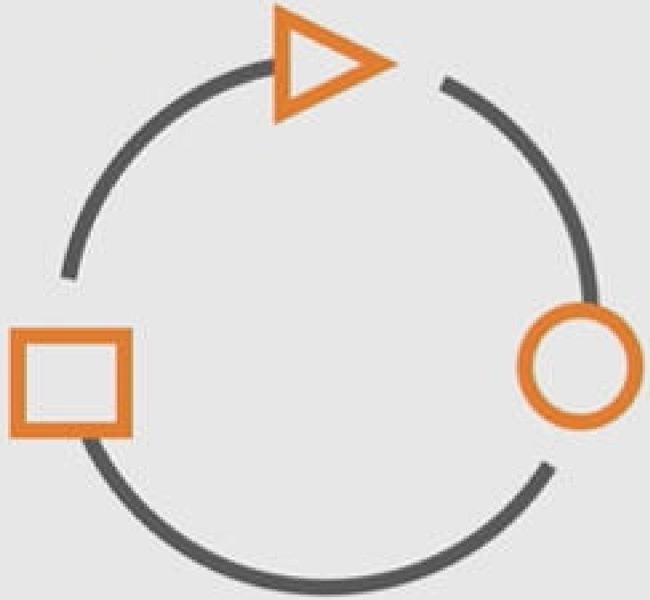
Import data from Amazon S3 buckets

Manually or automatically select algorithms

Evaluate accuracy metrics and deploy to production

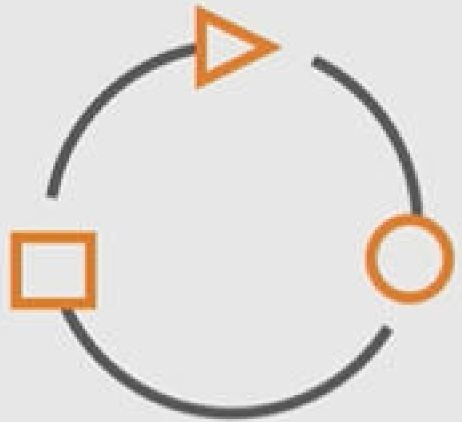
Visualize or export forecasts

Simplifying your data pipeline



- Automatically ingests new data when it's available and uses it for re-training
- Ability to schedule periodic model re-training and re-forecasting
- Allows for values and features to be overridden

Simplifying your data pipeline



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- Allows for values and features to be overridden

Machine learning automation

aws training and certification

Machine learning automation

aws training and certification

Amazon SageMaker and Amazon Forecast

aws training and certification

Amazon SageMaker

- Data needs to be converted for model training.
- Algorithm needs to be manually selected.
- Parameters require manual tuning for better accuracy.

Amazon Forecast

- No machine learning expertise needed
- Algorithm can be automatically selected
- Parameters are automatically tuned for maximum accuracy

Use cases

aws training and certification

Amazon Forecast works best with many related time-series and at least 1,000 data points, but it can still work for smaller data-sets.

Use cases

aws training and certification

Amazon Forecast works best with many related time-series and at least 1,000 data points, but it can still work for smaller data-sets.

Amazon Forecast is ideal for:

- Implementing tighter inventory control
- Web traffic forecasting
- Profit, sales, and expenses forecasting
- Resource and equipment forecasting

Use cases

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Key Takeaways

- Amazon Forecast leverages over a decade of experience in forecasting at Amazon.
- Comes with pre-built deep learning and traditional algorithms and automates the entire cleaning and model training process.
- Amazon Forecast incorporates external data and can generate forecasts for new time series where historical data is limited.

Key Takeaways

aws training and certification

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- Comes with pre-built deep learning and traditional algorithms and automates the entire cleaning and model training process.
- Amazon Forecast incorporates external data and can generate forecasts for new time series where historical data is limited.
- Visualizations may be accessed via the console, retrieved via API, or exported in CSV format.

In this course

- Service introduction
- Overview
- Demonstration
- Key takeaways

ML

aws training and certification

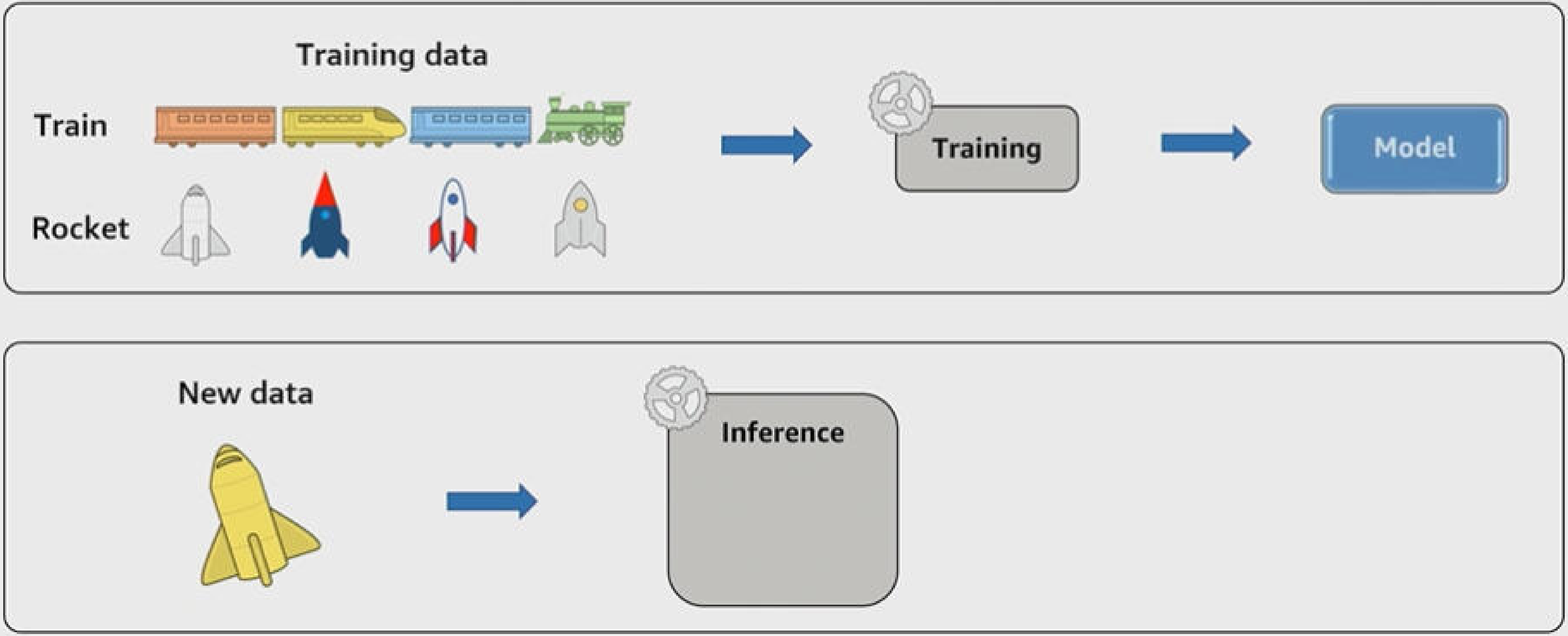
Methods and programs that:

Extract | Predict | Summarize | Optimize | Adapt

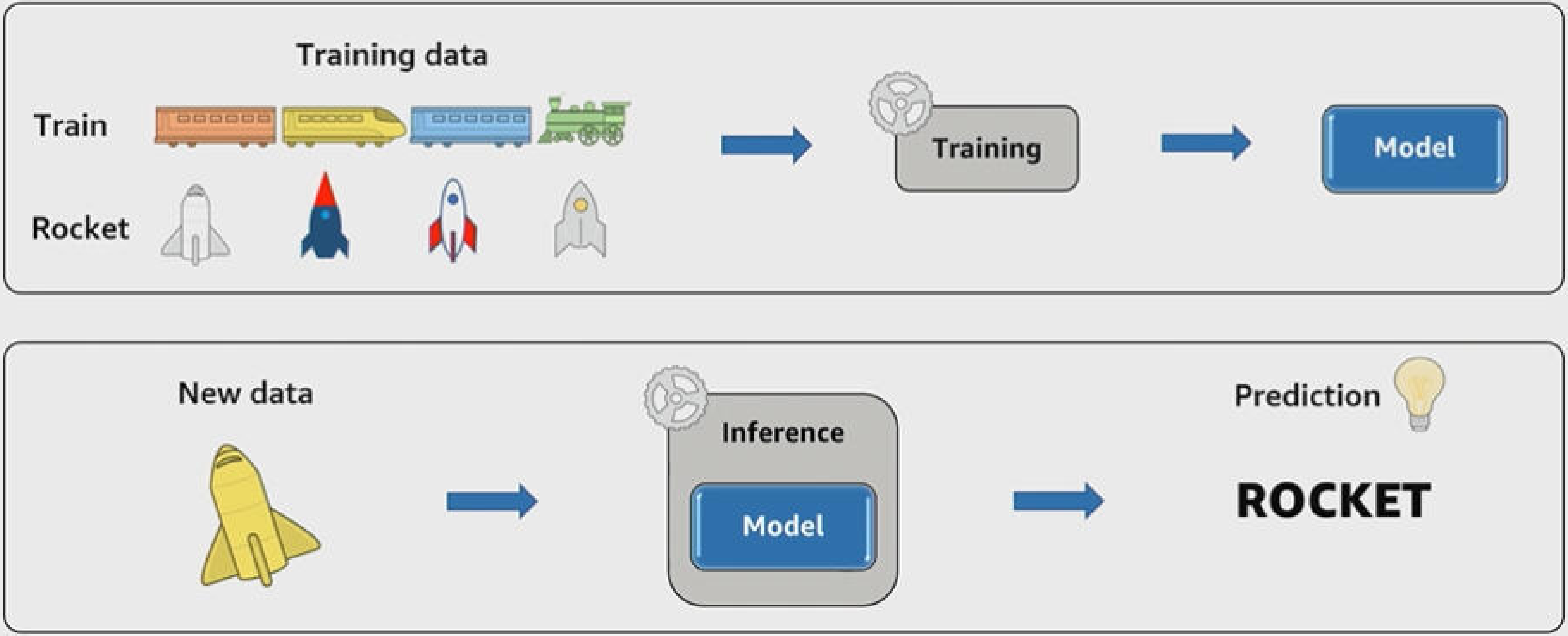
Your data + machine learning = smart applications

10:27

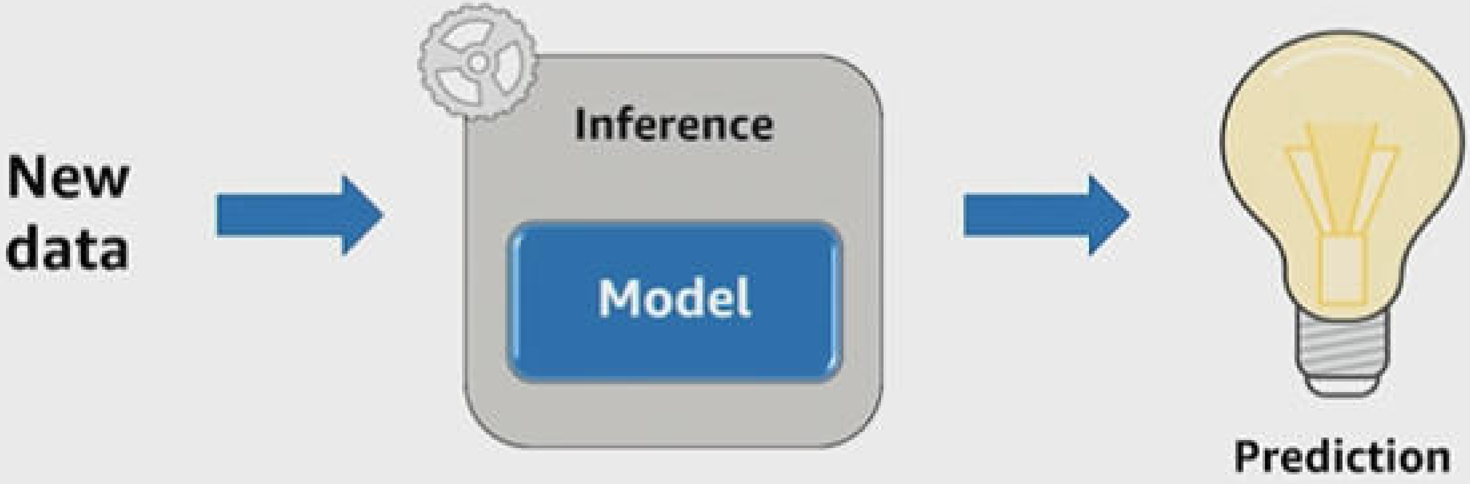
Training and inference



Training and inference



Inference



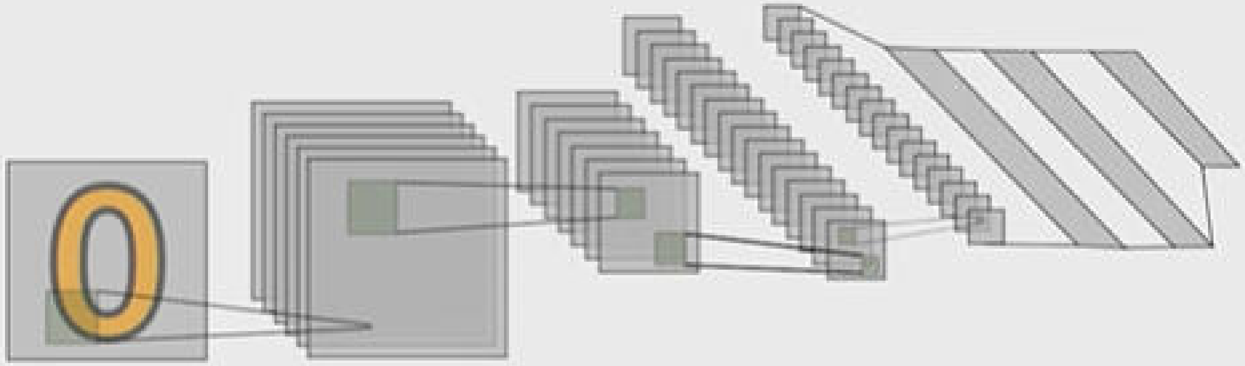
ML Challenge: Lower the Cost

aws training and certification

ML Challenge: Lower the Cost

aws training and certification

Convolutional neural network



ML Challenge: Lower the Cost

Model

Model

Model

10:27

ML Challenge: Lower the Cost

aws training and certification

– GPU
+ CPU
+ Memory

Model

Language understanding

Model

Model

Computer vision

ML Challenge: Lower the Cost

– GPU
+ CPU
+ Memory

Model

Language understanding

Model

+ GPU
– CPU
– Memory

Model

Computer vision

ML Challenge: Lower the Cost

– GPU
+ CPU
+ Memory

Model — Language understanding

Model

+ GPU
– CPU
– Memory

Model — Computer vision

ML Challenge: Lower the Cost

aws training and certification

– GPU
+ CPU
+ Memory

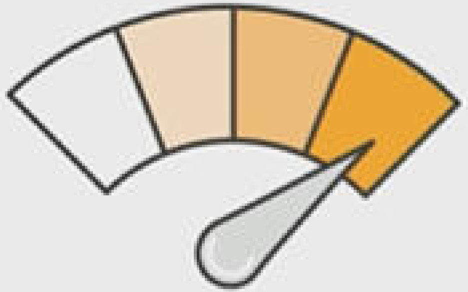
Model — Language understanding

Model

+ GPU
– CPU
– Memory

Model — Computer vision

Amazon EI



GPU-powered deep learning inference acceleration

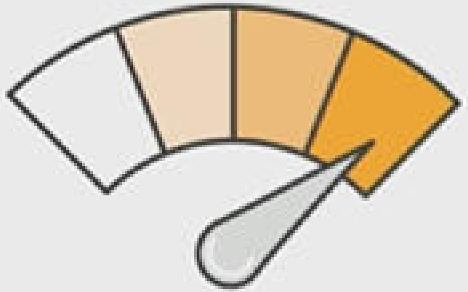
Fraction of the cost of standalone GPU instances

Amazon EI

GPU-powered deep learning inference acceleration

Fraction of the cost of standalone GPU instances

Amazon EI



GPU-powered deep learning inference acceleration

Fraction of the cost of standalone GPU instances

Amazon EI

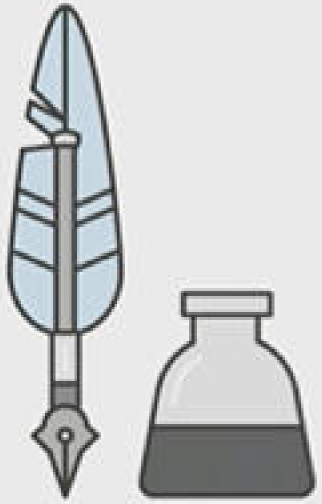
aws training and certification

Amazon EC2

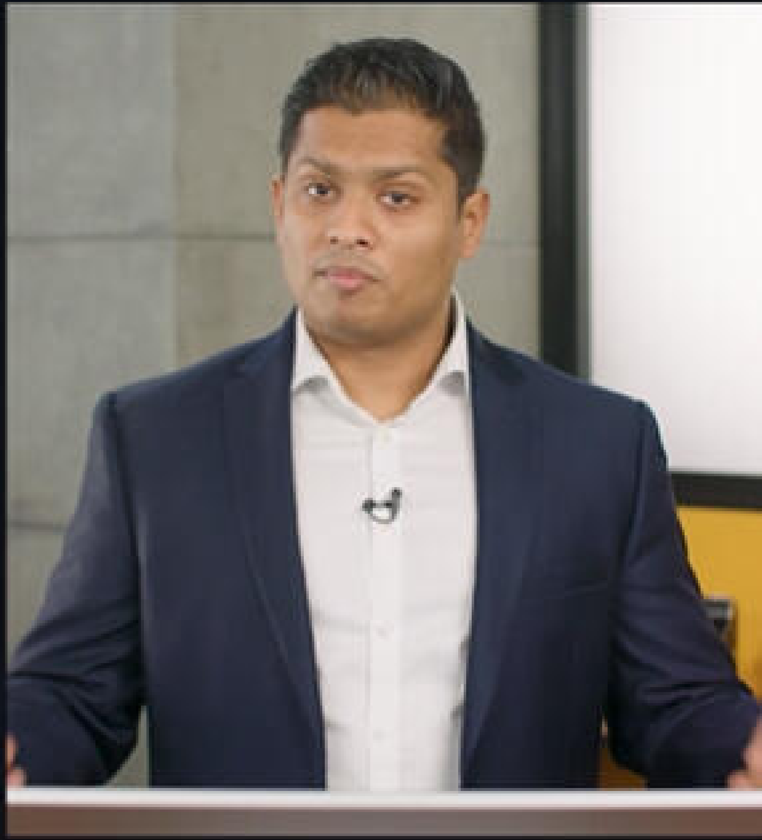
Amazon SageMaker

Overview

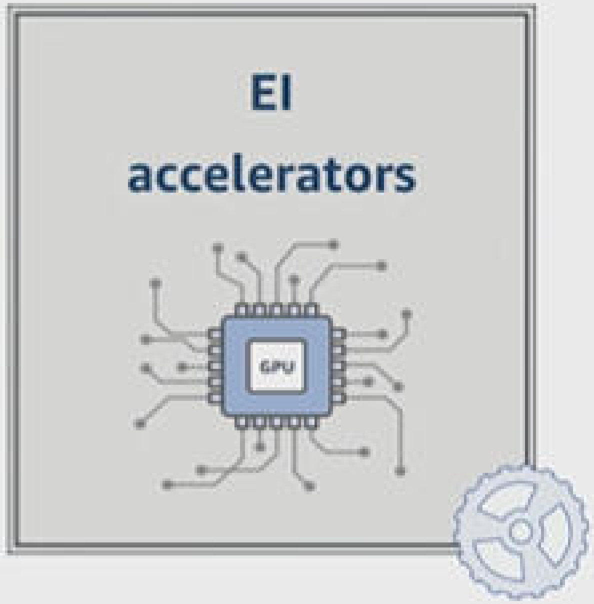
What is Amazon EI?

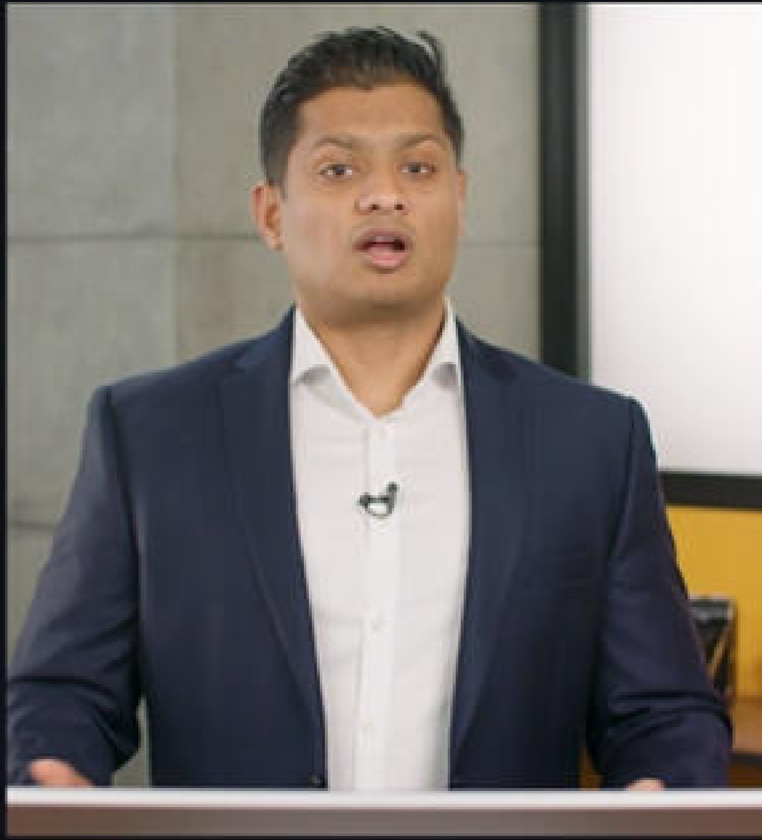


Accelerated compute service for Amazon SageMaker and Amazon EC2

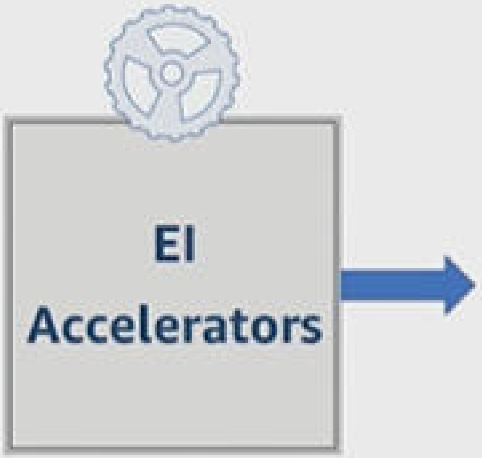


EI accelerators



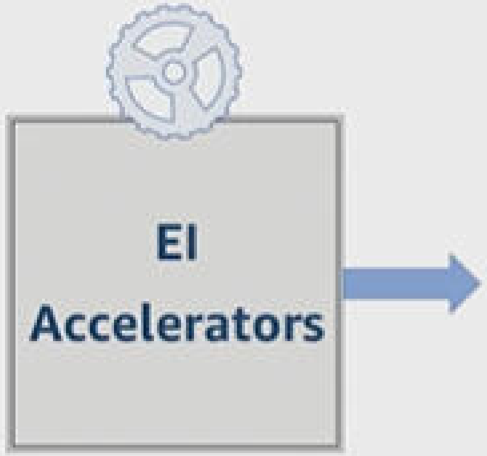


Benefits



Amazon Elastic Interference

Benefits



Amazon Elastic Interference

Reduce interference costs by up to 75%.

Benefits

aws training and certification

EI
Accelerators

Amazon Elastic
Interference

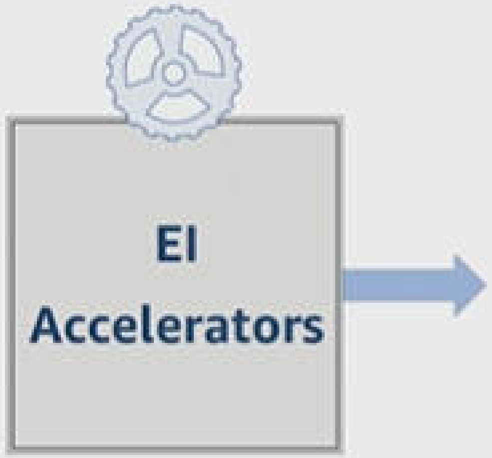
Reduce interference costs by up to **75%.**

Get exactly what you need.

TFLOPS: Tera Floating Operations Per Second

Benefits

aws training and certification



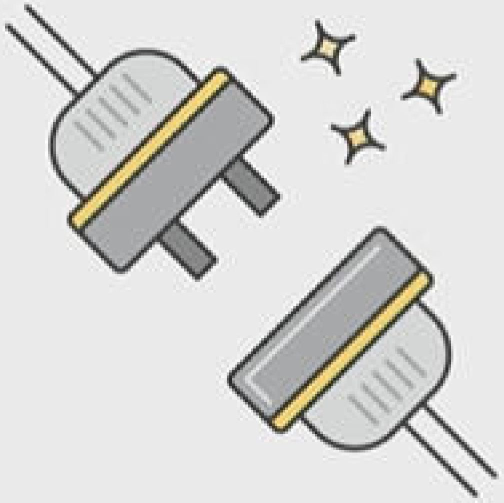
Amazon Elastic Interference

Reduce interference costs by up to **75%.**

Get exactly what you need.

Respond to changes in demand.

Key features



Integrated with Amazon SageMaker and Amazo

Key features

aws training and certification

TensorFlow™ ONNX mxnet

Model support

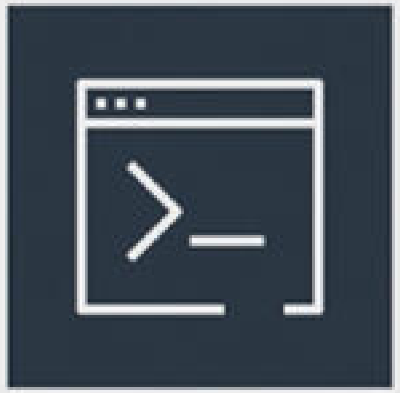
05:42

How does Amazon EI work?

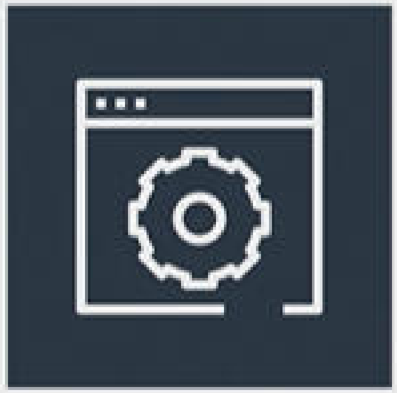
aws training and certification

Instances	Amazon-enhanced libraries	Models loaded	Inference calls
Instances communicate with accelerators	TensorFlow, mxnet: Model serving platforms for these frameworks automatically use EI accelerators	TensorFlow, MXNet, ONNX	Inference: Model

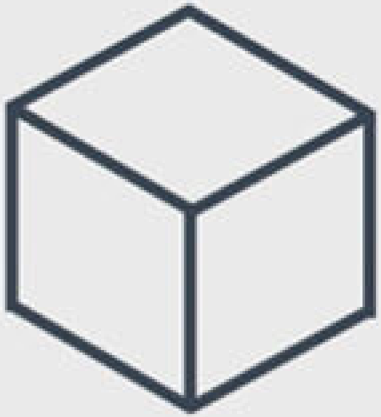
Amazon EI configuration



AWS Command Line Interface (AWS CLI)



AWS Management Console



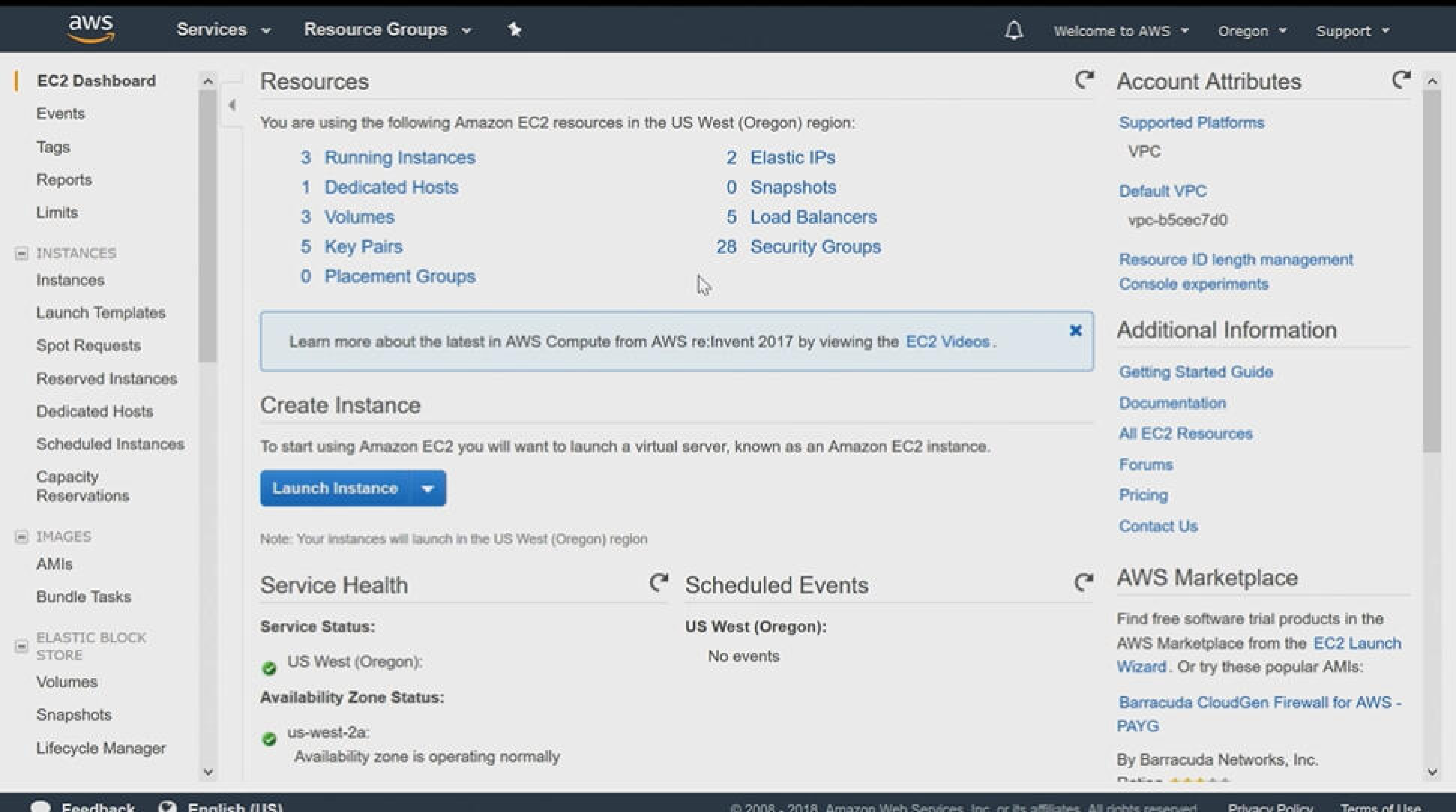
AWS SDK

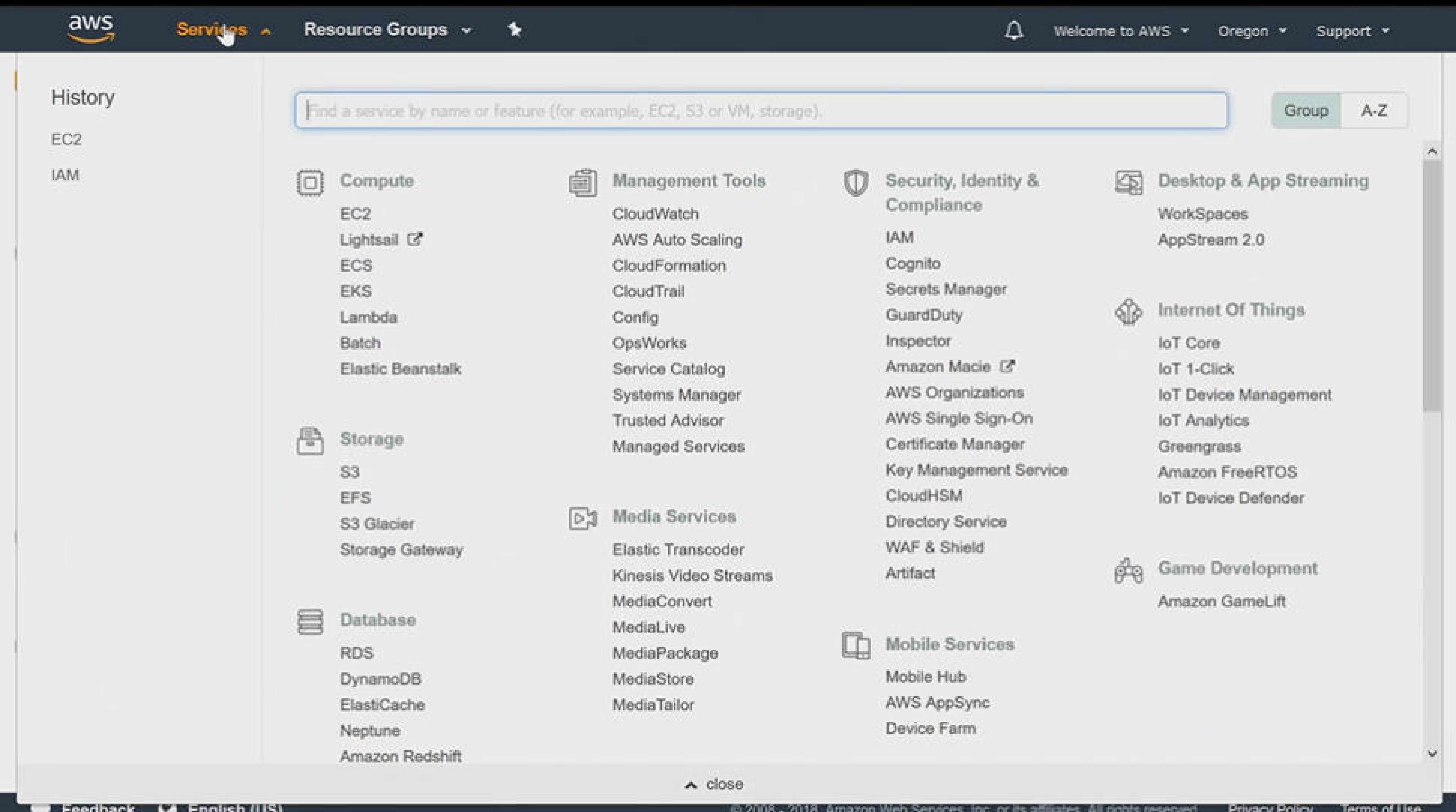
Amazon EI accelerator sizes

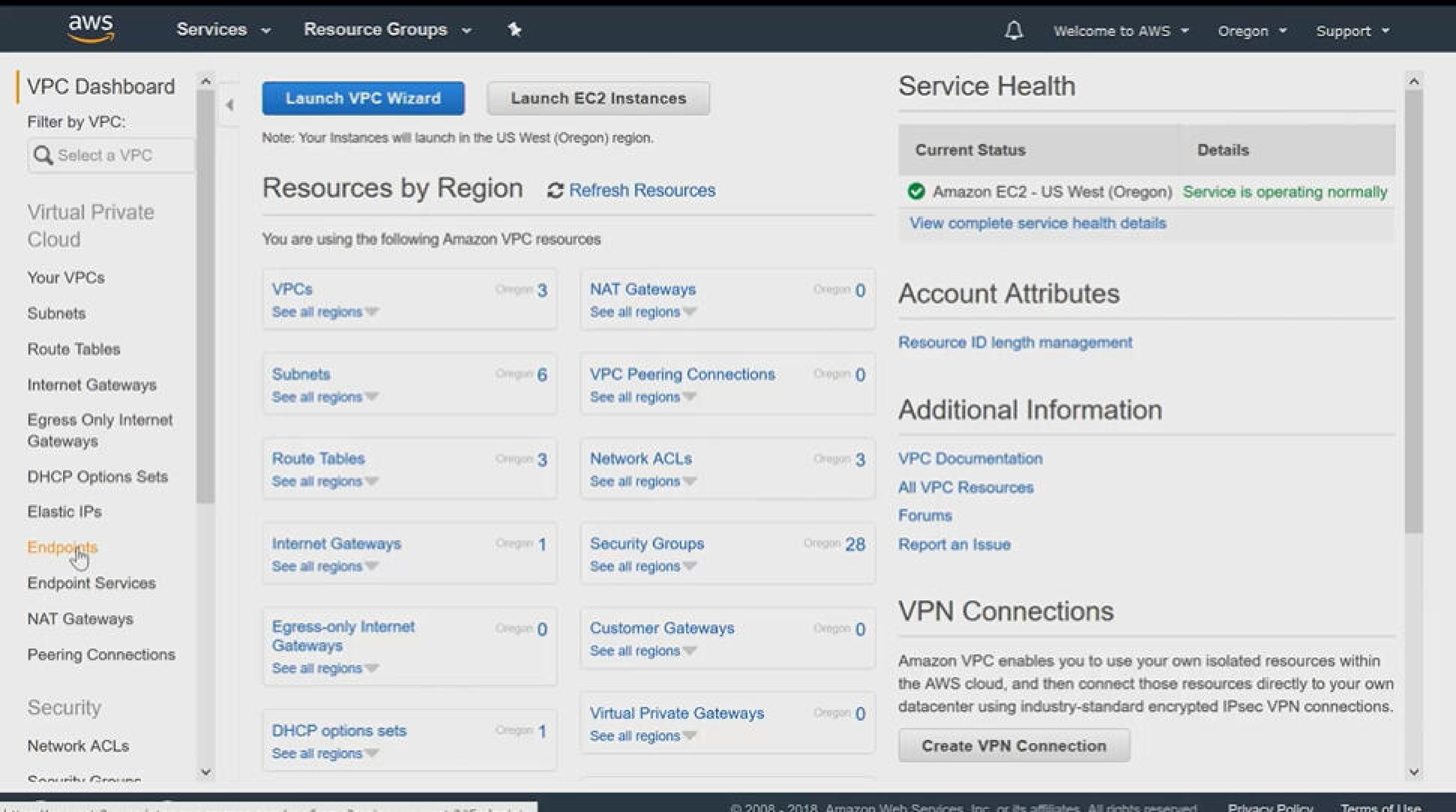
Accelerator Type	FP32 Throughput (TOPS)	FP16 Throughput (TOPS)	Memory (GB)
eia1.medium	1	8	1
eia1.large	2	16	2
eia1.xlarge	4	32	4

Demo

05:42


aws
Services
Resource Groups
Welcome to AWS
Oregon
Support
EC2 Dashboard
Events
Tags
Reports
Limits
INSTANCES
Instances
Launch Templates
Spot Requests
Reserved Instances
Dedicated Hosts
Scheduled Instances
Capacity Reservations
IMAGES
AMIs
Bundle Tasks
ELASTIC BLOCK STORE
Volumes
Snapshots
Lifecycle Manager
Resources
You are using the following Amazon EC2 resources in the US West (Oregon) region:
3 Running Instances
1 Dedicated Hosts
3 Volumes
5 Key Pairs
0 Placement Groups
2 Elastic IPs
0 Snapshots
5 Load Balancers
28 Security Groups
Learn more about the latest in AWS Compute from AWS re:Invent 2017 by viewing the EC2 Videos.
Create Instance
To start using Amazon EC2 you will want to launch a virtual server, known as an Amazon EC2 instance.
Launch Instance
Note: Your instances will launch in the US West (Oregon) region
Service Health
Service Status:
US West (Oregon):
Availability Zone Status:
us-west-2a:
Availability zone is operating normally
Scheduled Events
US West (Oregon):
No events
Account Attributes
Supported Platforms
VPC
Default VPC
vpc-b5cec7d0
Resource ID length management
Console experiments
Additional Information
Getting Started Guide
Documentation
All EC2 Resources
Forums
Pricing
Contact Us
AWS Marketplace
Find free software trial products in the AWS Marketplace from the EC2 Launch Wizard. Or try these popular AMIs:
Barracuda CloudGen Firewall for AWS - PAYG
By Barracuda Networks, Inc.
Feedback
English (US)
Privacy Policy
Terms of Use


aws
Services
Resource Groups
Welcome to AWS
Oregon
Support
History
EC2
IAM
Find a service by name or feature (for example, EC2, S3 or VM, storage).
Group
A-Z
Compute
EC2
Lightsail
ECS
EKS
Lambda
Batch
Elastic Beanstalk
Storage
S3
EFS
S3 Glacier
Storage Gateway
Database
RDS
DynamoDB
ElastiCache
Neptune
Amazon Redshift
Management Tools
CloudWatch
AWS Auto Scaling
CloudFormation
CloudTrail
Config
OpsWorks
Service Catalog
Systems Manager
Trusted Advisor
Managed Services
Media Services
Elastic Transcoder
Kinesis Video Streams
MediaConvert
MediaLive
MediaPackage
MediaStore
MediaTailor
Security, Identity & Compliance
IAM
Cognito
Secrets Manager
GuardDuty
Inspector
Amazon Macie
AWS Organizations
AWS Single Sign-On
Certificate Manager
Key Management Service
CloudHSM
Directory Service
WAF & Shield
Artifact
Mobile Services
Mobile Hub
AWS AppSync
Device Farm
Desktop & App Streaming
WorkSpaces
AppStream 2.0
Internet Of Things
IoT Core
IoT 1-Click
IoT Device Management
IoT Analytics
Greengrass
Amazon FreeRTOS
IoT Device Defender
Game Development
Amazon GameLift
close


aws
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Support
VPC Dashboard
Filter by VPC:
Select a VPC
Virtual Private Cloud
Your VPCs
Subnets
Route Tables
Internet Gateways
Egress Only Internet Gateways
DHCP Options Sets
Elastic IPs
Endpoints
Endpoint Services
NAT Gateways
Peering Connections
Security
Network ACLs
Launch VPC Wizard
Launch EC2 Instances
Note: Your Instances will launch in the US West (Oregon) region.
Resources by Region
Refresh Resources
You are using the following Amazon VPC resources
VPCs Oregon 3 See all regions
NAT Gateways Oregon 0 See all regions
Subnets Oregon 6 See all regions
VPC Peering Connections Oregon 0 See all regions
Route Tables Oregon 3 See all regions
Network ACLs Oregon 3 See all regions
Internet Gateways Oregon 1 See all regions
Security Groups Oregon 28 See all regions
Egress-only Internet Gateways Oregon 0 See all regions
Customer Gateways Oregon 0 See all regions
DHCP options sets Oregon 1 See all regions
Virtual Private Gateways Oregon 0 See all regions
Service Health
Current Status
Details
Amazon EC2 - US West (Oregon)
Service is operating normally
View complete service health details
Account Attributes
Resource ID length management
Additional Information
VPC Documentation
All VPC Resources
Forums
Report an Issue
VPN Connections
Amazon VPC enables you to use your own isolated resources within the AWS cloud, and then connect those resources directly to your own datacenter using industry-standard encrypted IPsec VPN connections.
Create VPN Connection
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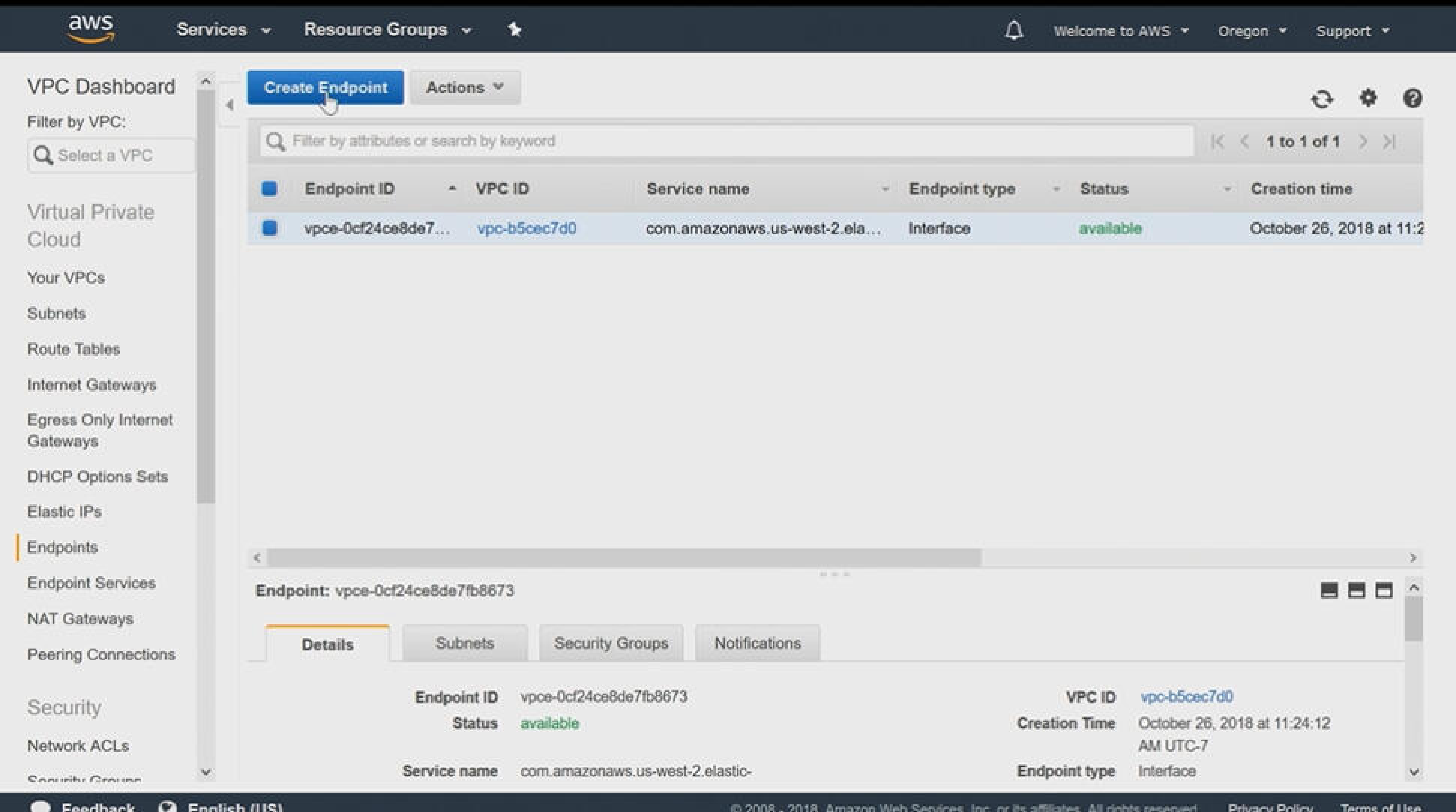
Privacy Policy
Terms of Use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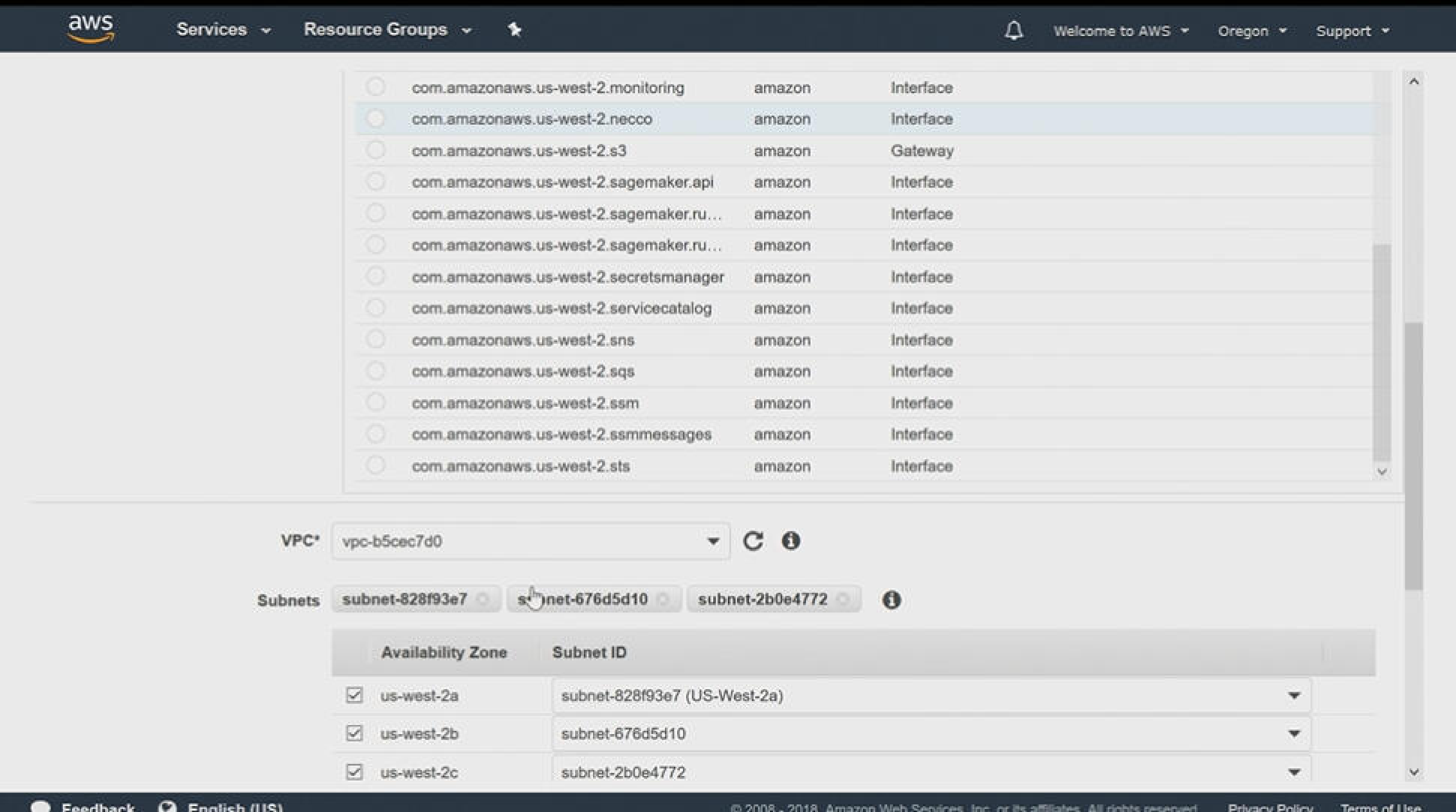
Peering Connections
Security
Network ACLs
Create Endpoint
Actions
Filter by attributes or search by keyword
1 to 1 of 1
Endpoint ID
VPC ID
Service name
Endpoint type
Status
Creation time
vpce-0cf24ce8de7...
vpc-b5cec7d0
com.amazonaws.us-west-2.ela...
Interface
available
October 26, 2018 at 11:2
Endpoint: vpce-0cf24ce8de7fb8673
Details
Subnets
Security Groups
Notifications
Endpoint ID
vpce-0cf24ce8de7fb8673
Status
available
Service name
com.amazonaws.us-west-2.elastic-
VPC ID
vpc-b5cec7d0
Creation Time
October 26, 2018 at 11:24:12 AM UTC-7
Endpoint type
Interface
Feedback
English (US)
Privacy Policy
Terms of Use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com.amazonaws.us-west-2.monitoring amazon Interface
com.amazonaws.us-west-2.necco amazon Interface
com.amazonaws.us-west-2.s3 amazon Gateway
com.amazonaws.us-west-2.sagemaker.api amazon Interface
com.amazonaws.us-west-2.sagemaker.ru... amazon Interface
com.amazonaws.us-west-2.sagemaker.ru... amazon Interface
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com.amazonaws.us-west-2.sqs amazon Interface
com.amazonaws.us-west-2.ssm amazon Interface
com.amazonaws.us-west-2.ssmmessages amazon Interface
com.amazonaws.us-west-2.sts amazon Interface
VPC*
vpc-b5cec7d0
Subnets
subnet-828f93e7
subnet-2b0e4772
Availability Zone
Subnet ID
us-west-2a
subnet-828f93e7 (US-West-2a)
us-west-2b
subnet-676d5d10
us-west-2c
subnet-2b0e4772
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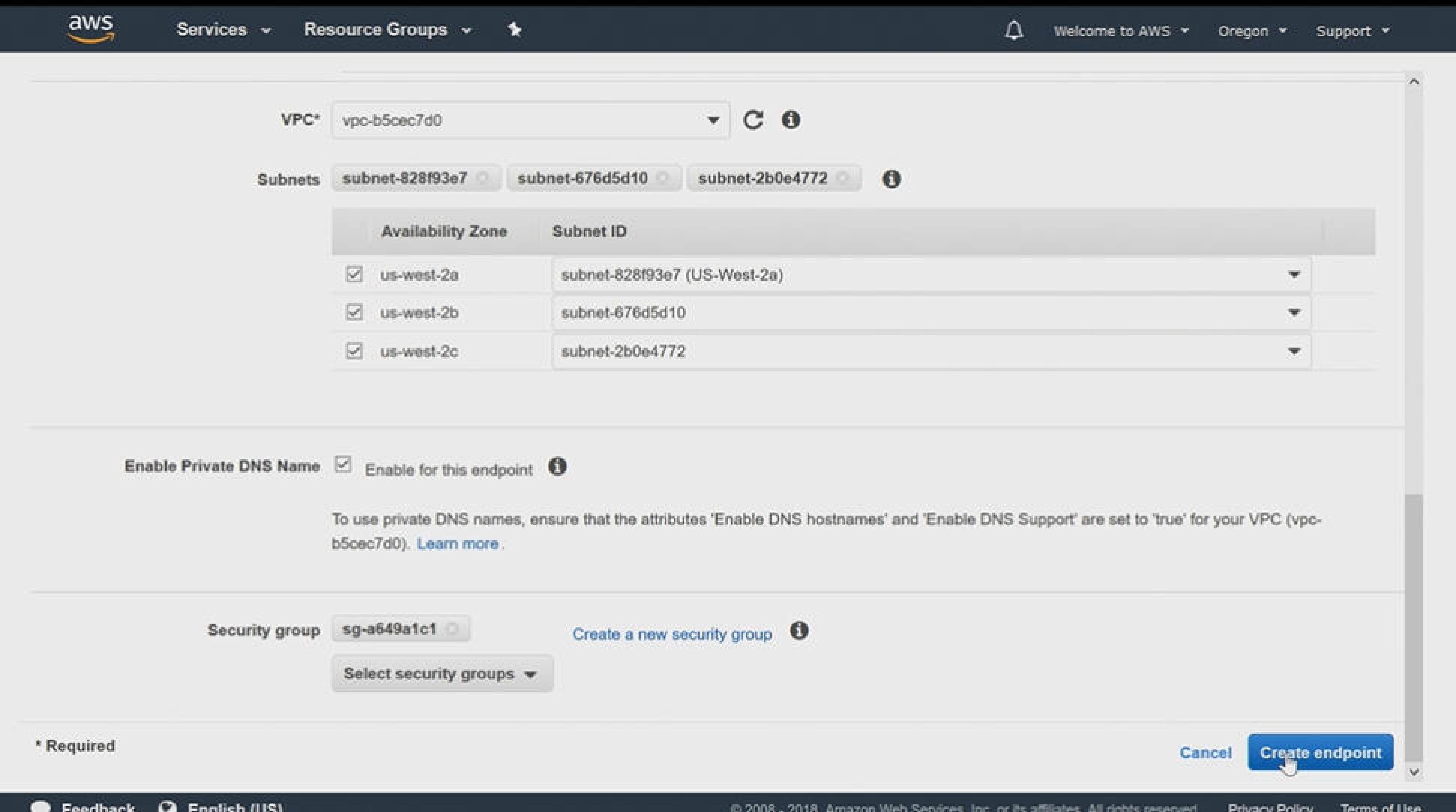
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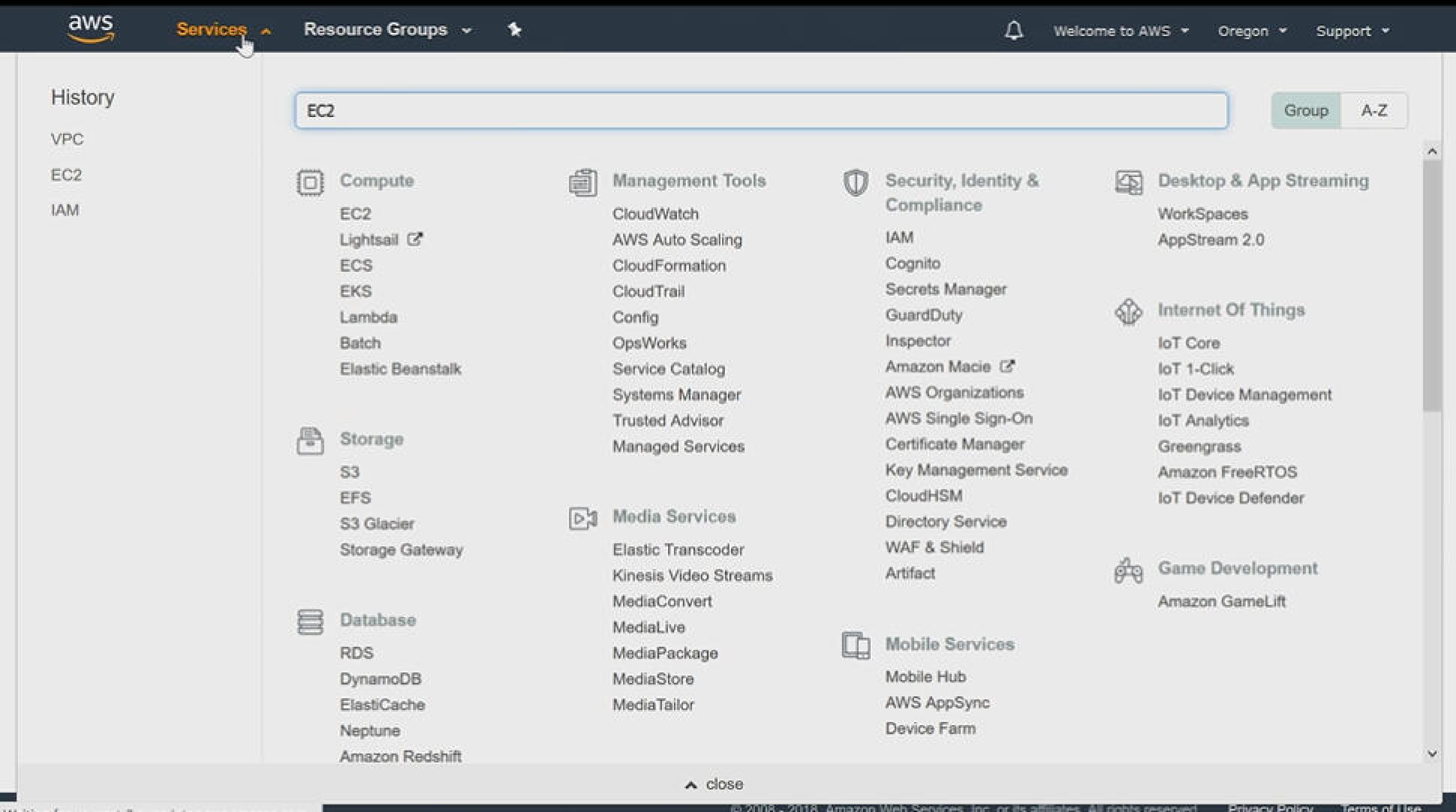
VPC*
vpc-b5cec7d0
Subnets
subnet-828f93e7
subnet-676d5d10
subnet-2b0e4772
Availability Zone
Subnet ID
us-west-2a
subnet-828f93e7 (US-West-2a)
us-west-2b
subnet-676d5d10
us-west-2c
subnet-2b0e4772
Enable Private DNS Name
Enable for this endpoint
To use private DNS names, ensure that the attributes 'Enable DNS hostnames' and 'Enable DNS Support' are set to 'true' for your VPC (vpc-b5cec7d0). Learn more.
Security group
sg-a649a1c1
Create a new security group
Select security groups
* Required
Cancel
Create endpoint
Feedback
English (US)
Privacy Policy
Terms of Use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EKS
Lambda
Batch
Elastic Beanstalk
Storage
S3
EFS
S3 Glacier
Storage Gateway
Database
RDS
DynamoDB
ElastiCache
Neptune
Amazon Redshift
Management Tools
CloudWatch
AWS Auto Scaling
CloudFormation
CloudTrail
Config
OpsWorks
Service Catalog
Systems Manager
Trusted Advisor
Managed Services
Media Services
Elastic Transcoder
Kinesis Video Streams
MediaConvert
MediaLive
MediaPackage
MediaStore
MediaTailor
Security, Identity & Compliance
IAM
Cognito
Secrets Manager
GuardDuty
Inspector
Amazon Macie
AWS Organizations
AWS Single Sign-On
Certificate Manager
Key Management Service
CloudHSM
Directory Service
WAF & Shield
Artifact
Mobile Services
Mobile Hub
AWS AppSync
Device Farm
Desktop & App Streaming
WorkSpaces
AppStream 2.0
Internet Of Things
IoT Core
IoT 1-Click
IoT Device Management
IoT Analytics
Greengrass
Amazon FreeRTOS
IoT Device Defender
Game Development
Amazon GameLift
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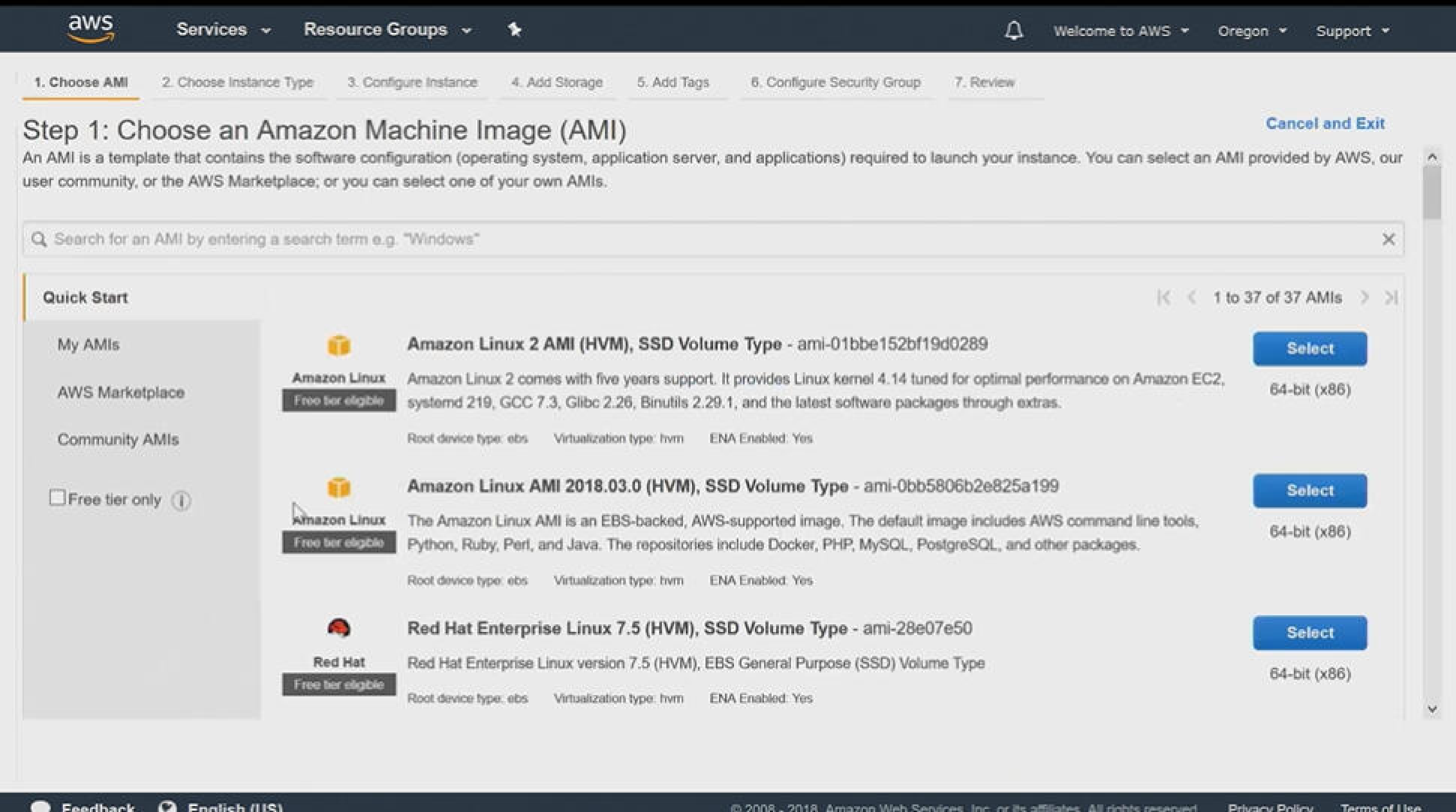
aws
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Welcome to AWS
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Support
1. Choose AMI
2. Choose Instance Type
3. Configure Instance
4. Add Storage
5. Add Tags
6. Configure Security Group
7. Review
Step 1: Choose an Amazon Machine Image (AMI)
Cancel and Exit
An AMI is a template that contains the software configuration (operating system, application server, and applications) required to launch your instance. You can select an AMI provided by AWS, our user community, or the AWS Marketplace; or you can select one of your own AMIs.
Search for an AMI by entering a search term e.g. "Windows"
Quick Start
1 to 37 of 37 AMIs
My AMIs
AWS Marketplace
Community AMIs
Free tier only
Amazon Linux 2 AMI (HVM), SSD Volume Type - ami-01bbe152bf19d0289
Amazon Linux
Free tier eligible
Amazon Linux 2 comes with five years support. It provides Linux kernel 4.14 tuned for optimal performance on Amazon EC2, systemd 219, GCC 7.3, Glibc 2.26, Binutils 2.29.1, and the latest software packages through extras.
Root device type: ebs
Virtualization type: hvm
ENA Enabled: Yes
Select
64-bit (x86)
Amazon Linux AMI 2018.03.0 (HVM), SSD Volume Type - ami-0bb5806b2e825a199
Amazon Linux
Free tier eligible
The Amazon Linux AMI is an EBS-backed, AWS-supported image. The default image includes AWS command line tools, Python, Ruby, Perl, and Java. The repositories include Docker, PHP, MySQL, PostgreSQL, and other packages.
Root device type: ebs
Virtualization type: hvm
ENA Enabled: Yes
Select
64-bit (x86)
Red Hat Enterprise Linux 7.5 (HVM), SSD Volume Type - ami-28e07e50
Red Hat
Free tier eligible
Red Hat Enterprise Linux version 7.5 (HVM), EBS General Purpose (SSD) Volume Type
Root device type: ebs
Virtualization type: hvm
ENA Enabled: Yes
Select
64-bit (x86)
Feedback
English (US)
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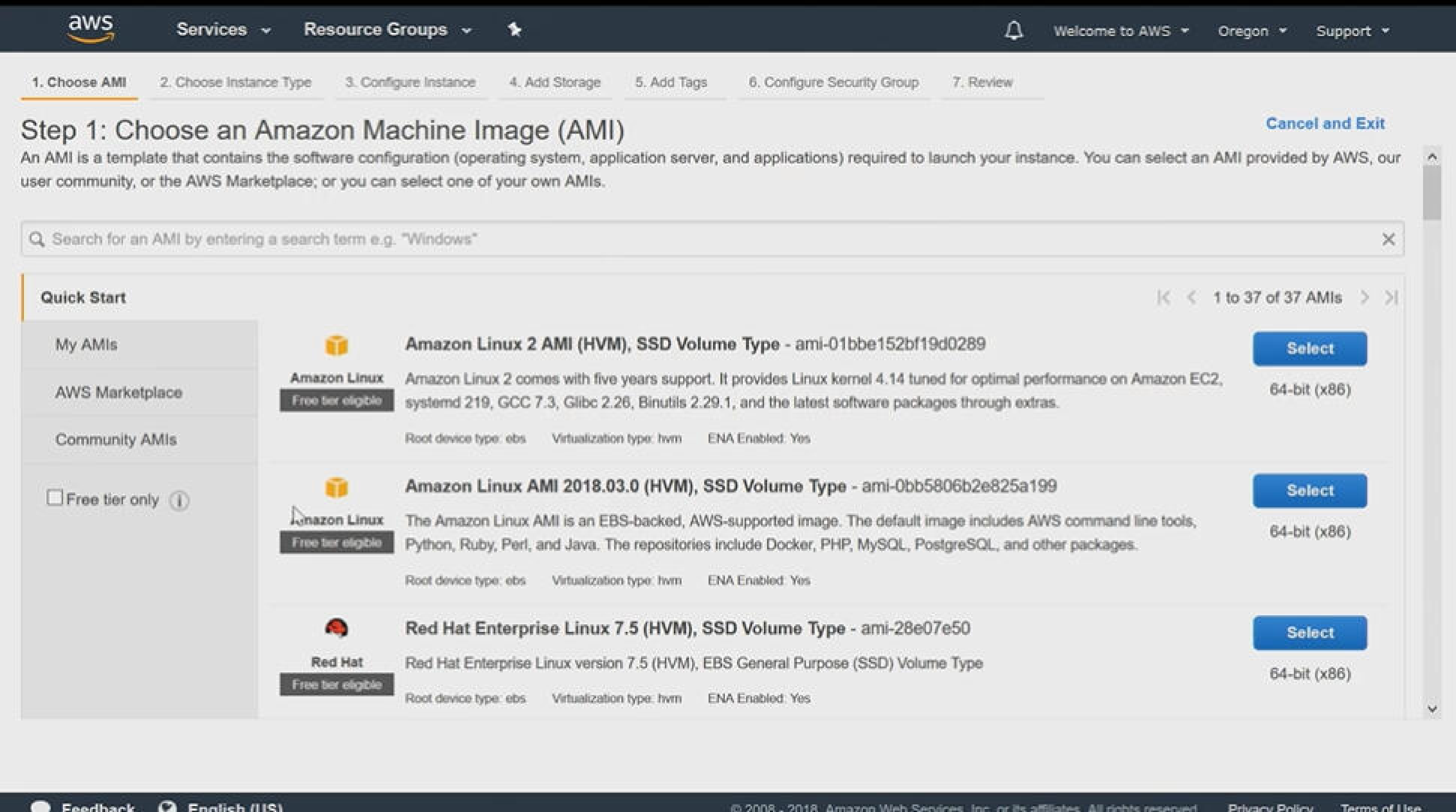
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64-bit (x86)
Red Hat
Free tier eligible
Red Hat Enterprise Linux 7.5 (HVM), SSD Volume Type - ami-28e07e50
Red Hat Enterprise Linux version 7.5 (HVM), EBS General Purpose (SSD) Volume Type
Root device type: ebs
Virtualization type: hvm
ENA Enabled: Yes
Select
64-bit (x86)
Feedback
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Services Resource Groups Welcome to AWS Oregon Support

1. Choose AMI 2. Choose Instance Type 3. Configure Instance 4. Add Storage 5. Add Tags 6. Configure Security Group 7. Review

Step 2: Choose an Instance Type

	General purpose	t2.large	2	8	EBS only	-	Low to Moderate	Yes
	General purpose	t2.xlarge	4	16	EBS only	-	Moderate	Yes
	General purpose	t2.2xlarge	8	32	EBS only	-	Moderate	Yes
	General purpose	t3a.nano	2	0.5	EBS only	Yes	Up to 5 Gigabit	Yes
	General purpose	t3a.micro	2	1	EBS only	Yes	Up to 5 Gigabit	Yes
	General purpose	t3a.small	2	2	EBS only	Yes	Up to 5 Gigabit	Yes
	General purpose	t3a.medium	2	4	EBS only	Yes	Up to 5 Gigabit	Yes
	General purpose	t3a.large	2	8	EBS only	Yes	Up to 5 Gigabit	Yes
	General purpose	t3a.xlarge	4	16	EBS only	Yes	Up to 5 Gigabit	Yes
	General purpose	t3a.2xlarge	8	32	EBS only	Yes	Up to 5 Gigabit	Yes
	General purpose	t3.nano	2	0.5	EBS only	Yes	Up to 5 Gigabit	Yes
	General purpose	t3.micro	2	1	EBS only	Yes	Up to 5 Gigabit	Yes

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1. Choose AMI 2. Choose Instance Type 3. Configure Instance 4. Add Storage 5. Add Tags 6. Configure Security Group 7. Review

Step 2: Choose an Instance Type

General purpose	t3.micro	2	1	EBS only	Yes	Up to 5 Gigabit	Yes
General purpose	t3.small	2	2	EBS only	Yes	Up to 5 Gigabit	Yes
General purpose	t3.medium	2	4	EBS only	Yes	Up to 5 Gigabit	Yes
General purpose	t3.large	2	8	EBS only	Yes	Up to 5 Gigabit	Yes
General purpose	t3.xlarge	4	16	EBS only	Yes	Up to 5 Gigabit	Yes
General purpose	t3.2xlarge	8	32	EBS only	Yes	Up to 5 Gigabit	Yes
General purpose	m5ad.large	2	8	1 x 75 (SSD)	Yes	Up to 10 Gigabit	Yes
General purpose	m5ad.xlarge	4	16	1 x 150 (SSD)	Yes	Up to 10 Gigabit	Yes
General purpose	m5ad.2xlarge	8	32	1 x 300 (SSD)	Yes	Up to 10 Gigabit	Yes
General purpose	m5ad.4xlarge	16	64	2 x 300 (SSD)	Yes	Up to 10 Gigabit	Yes
General purpose	m5ad.12xlarge	48	192	2 x 900 (SSD)	Yes	10 Gigabit	Yes
General purpose	m5ad.24xlarge	96	384	4 x 900 (SSD)	Yes	20 Gigabit	Yes

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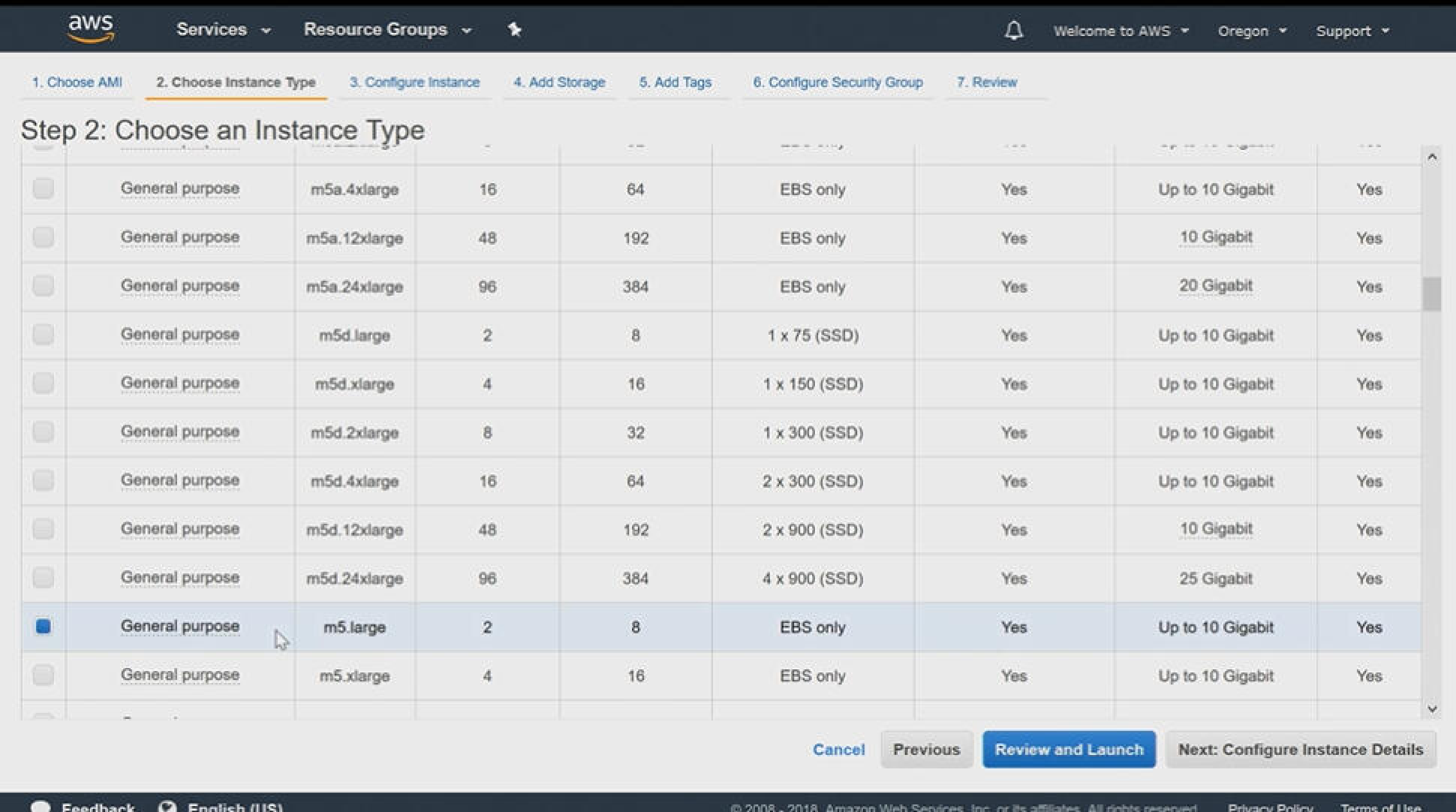
Step 2: Choose an Instance Type

General purpose	t3.xlarge	4	16	EBS only	Yes	Up to 5 Gigabit	Yes
General purpose	t3.2xlarge	8	32	EBS only	Yes	Up to 5 Gigabit	Yes
General purpose	m5ad.large	2	8	1 x 75 (SSD)	Yes	Up to 10 Gigabit	Yes
General purpose	m5ad.xlarge	4	16	1 x 150 (SSD)	Yes	Up to 10 Gigabit	Yes
General purpose	m5ad.2xlarge	8	32	1 x 300 (SSD)	Yes	Up to 10 Gigabit	Yes
General purpose	m5ad.4xlarge	16	64	2 x 300 (SSD)	Yes	Up to 10 Gigabit	Yes
General purpose	m5ad.12xlarge	48	192	2 x 900 (SSD)	Yes	10 Gigabit	Yes
General purpose	m5ad.24xlarge	96	384	4 x 900 (SSD)	Yes	20 Gigabit	Yes
General purpose	m5a.large	2	8	EBS only	Yes	Up to 10 Gigabit	Yes
General purpose	m5a.xlarge	4	16	EBS only	Yes	Up to 10 Gigabit	Yes
General purpose	m5a.2xlarge	8	32	EBS only	Yes	Up to 10 Gigabit	Yes
General purpose	m5a.4xlarge	16	64	EBS only	Yes	Up to 10 Gigabit	Yes

Cancel | Previous | Review and Launch | Next: Configure Instance Details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7. Review
Step 2: Choose an Instance Type
General purpose m5a.4xlarge 16 64 EBS only Yes Up to 10 Gigabit Yes
General purpose m5a.12xlarge 48 192 EBS only Yes 10 Gigabit Yes
General purpose m5a.24xlarge 96 384 EBS only Yes 20 Gigabit Yes
General purpose m5d.large 2 8 1 x 75 (SSD) Yes Up to 10 Gigabit Yes
General purpose m5d.xlarge 4 16 1 x 150 (SSD) Yes Up to 10 Gigabit Yes
General purpose m5d.2xlarge 8 32 1 x 300 (SSD) Yes Up to 10 Gigabit Yes
General purpose m5d.4xlarge 16 64 2 x 300 (SSD) Yes Up to 10 Gigabit Yes
General purpose m5d.12xlarge 48 192 2 x 900 (SSD) Yes 10 Gigabit Yes
General purpose m5d.24xlarge 96 384 4 x 900 (SSD) Yes 25 Gigabit Yes
General purpose m5.large 2 8 EBS only Yes Up to 10 Gigabit Yes
General purpose m5.xlarge 4 16 EBS only Yes Up to 10 Gigabit Yes
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aws Services Resource Groups Welcome to AWS Oregon Support

1. Choose AMI | 2. Choose Instance Type | 3. Configure Instance | 4. Add Storage | 5. Add Tags | 6. Configure Security Group | 7. Review

Step 2: Choose an Instance Type

☐	General purpose	m5a.4xlarge	16	64	EBS only	Yes	Up to 10 Gigabit	Yes
☐	General purpose	m5a.12xlarge	48	192	EBS only	Yes	10 Gigabit	Yes
☐	General purpose	m5a.24xlarge	96	384	EBS only	Yes	20 Gigabit	Yes
☐	General purpose	m5d.large	2	8	1 x 75 (SSD)	Yes	Up to 10 Gigabit	Yes
☐	General purpose	m5d.xlarge	4	16	1 x 150 (SSD)	Yes	Up to 10 Gigabit	Yes
☐	General purpose	m5d.2xlarge	8	32	1 x 300 (SSD)	Yes	Up to 10 Gigabit	Yes
☐	General purpose	m5d.4xlarge	16	64	2 x 300 (SSD)	Yes	Up to 10 Gigabit	Yes
☐	General purpose	m5d.12xlarge	48	192	2 x 900 (SSD)	Yes	10 Gigabit	Yes
☐	General purpose	m5d.24xlarge	96	384	4 x 900 (SSD)	Yes	25 Gigabit	Yes
☑	General purpose	m5.large	2	8	EBS only	Yes	Up to 10 Gigabit	Yes
☐	General purpose	m5.xlarge	4	16	EBS only	Yes	Up to 10 Gigabit	Yes

Cancel | Previous | Review and Launch | Next: Configure Instance Details

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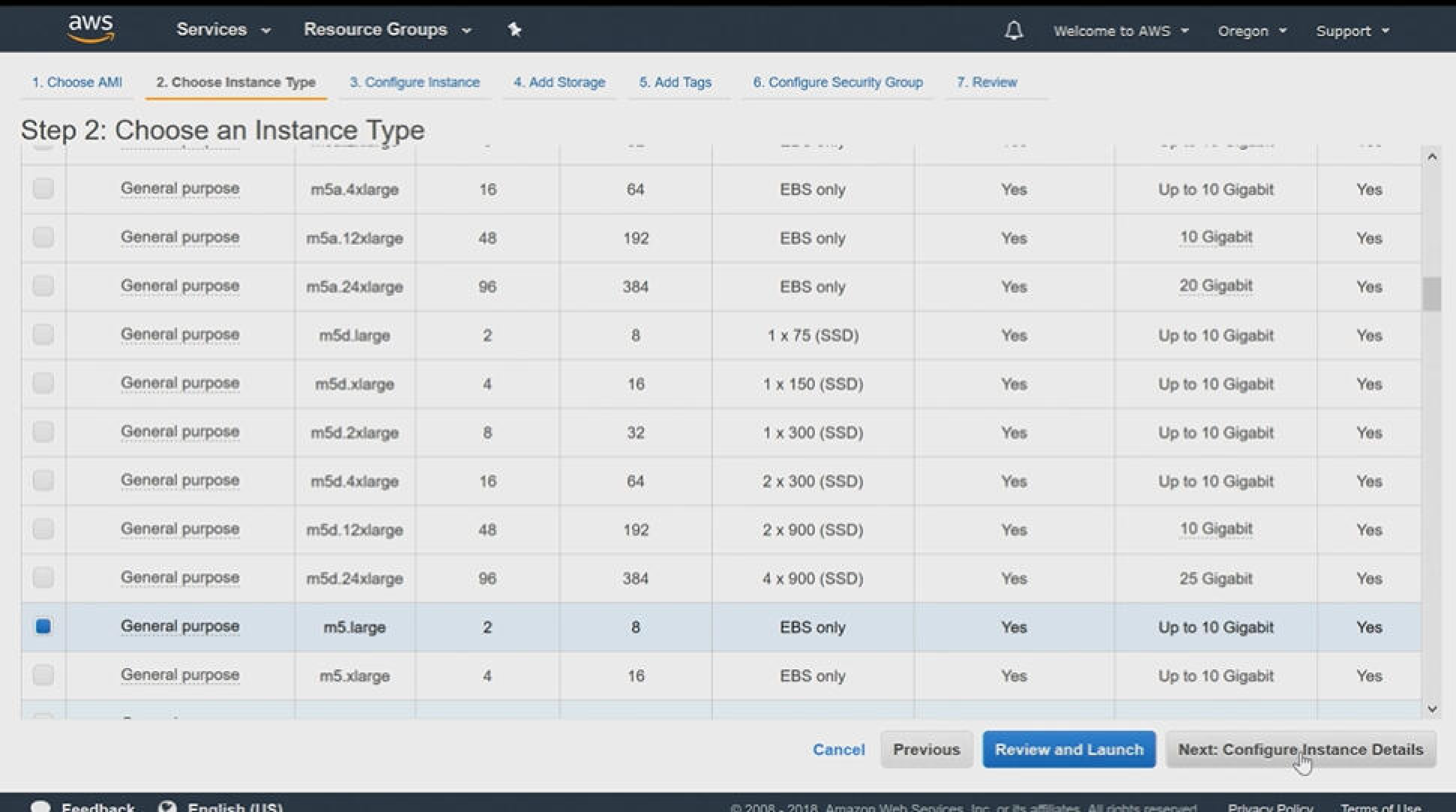
1. Choose AMI | 2. Choose Instance Type | 3. Configure Instance | 4. Add Storage | 5. Add Tags | 6. Configure Security Group | 7. Review

Step 2: Choose an Instance Type

☐	General purpose	m5a.4xlarge	16	64	EBS only	Yes	Up to 10 Gigabit	Yes
☐	General purpose	m5a.12xlarge	48	192	EBS only	Yes	10 Gigabit	Yes
☐	General purpose	m5a.24xlarge	96	384	EBS only	Yes	20 Gigabit	Yes
☐	General purpose	m5d.large	2	8	1 x 75 (SSD)	Yes	Up to 10 Gigabit	Yes
☐	General purpose	m5d.xlarge	4	16	1 x 150 (SSD)	Yes	Up to 10 Gigabit	Yes
☐	General purpose	m5d.2xlarge	8	32	1 x 300 (SSD)	Yes	Up to 10 Gigabit	Yes
☐	General purpose	m5d.4xlarge	16	64	2 x 300 (SSD)	Yes	Up to 10 Gigabit	Yes
☐	General purpose	m5d.12xlarge	48	192	2 x 900 (SSD)	Yes	10 Gigabit	Yes
☐	General purpose	m5d.24xlarge	96	384	4 x 900 (SSD)	Yes	25 Gigabit	Yes
■	General purpose	m5.large	2	8	EBS only	Yes	Up to 10 Gigabit	Yes
☐	General purpose	m5.xlarge	4	16	EBS only	Yes	Up to 10 Gigabit	Yes

Cancel | Previous | Review and Launch | Next: Configure Instance Details


aws
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Step 2: Choose an Instance Type
General purpose m5a.4xlarge 16 64 EBS only Yes Up to 10 Gigabit Yes
General purpose m5a.12xlarge 48 192 EBS only Yes 10 Gigabit Yes
General purpose m5a.24xlarge 96 384 EBS only Yes 20 Gigabit Yes
General purpose m5d.large 2 8 1 x 75 (SSD) Yes Up to 10 Gigabit Yes
General purpose m5d.xlarge 4 16 1 x 150 (SSD) Yes Up to 10 Gigabit Yes
General purpose m5d.2xlarge 8 32 1 x 300 (SSD) Yes Up to 10 Gigabit Yes
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General purpose m5d.12xlarge 48 192 2 x 900 (SSD) Yes 10 Gigabit Yes
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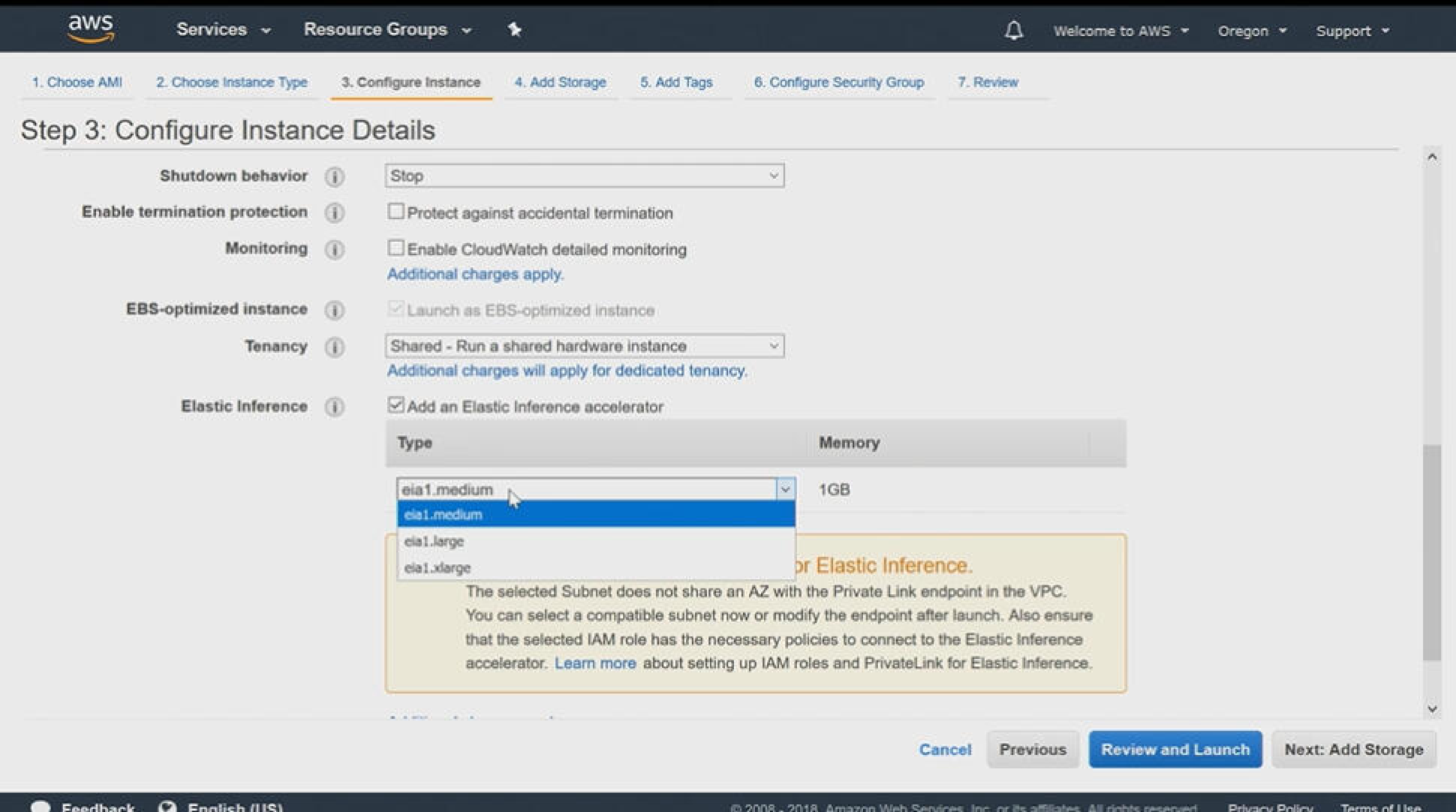
General purpose m5.large 2 8 EBS only Yes Up to 10 Gigabit Yes
General purpose m5.xlarge 4 16 EBS only Yes Up to 10 Gigabit Yes
Cancel
Previous
Review and Launch
Next: Configure Instance Details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Step 3: Configure Instance Details
Shutdown behavior
Stop
Enable termination protection
Protect against accidental termination
Monitoring
Enable CloudWatch detailed monitoring
Additional charges apply.
EBS-optimized instance
Launch as EBS-optimized instance
Tenancy
Shared - Run a shared hardware instance
Additional charges will apply for dedicated tenancy.
Elastic Inference
Add an Elastic Inference accelerator
Type
Memory
eia1.medium
1GB
eia1.medium
eia1.large
eia1.xlarge
r Elastic Inference.
The selected Subnet does not share an AZ with the Private Link endpoint in the VPC.
You can select a compatible subnet now or modify the endpoint after launch. Also ensure
that the selected IAM role has the necessary policies to connect to the Elastic Inference
accelerator. Learn more about setting up IAM roles and PrivateLink for Elastic Inference.
Cancel
Previous
Review and Launch
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Feedback
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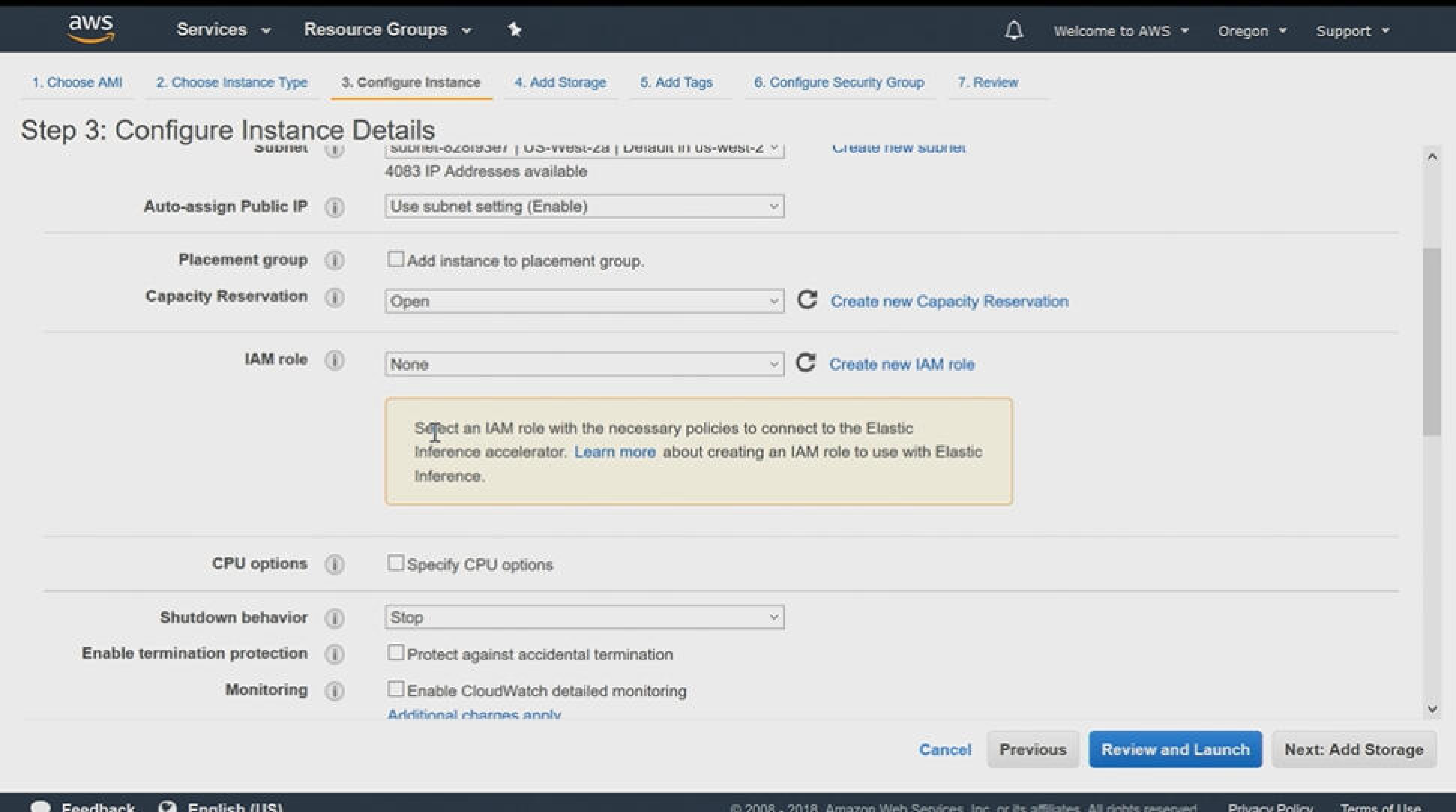
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6. Configure Security Group
7. Review
Step 3: Configure Instance Details
Subnet
Create new subnet
4083 IP Addresses available
Auto-assign Public IP
Use subnet setting (Enable)
Placement group
Add instance to placement group.
Capacity Reservation
Open
Create new Capacity Reservation
IAM role
None
Create new IAM role
Select an IAM role with the necessary policies to connect to the Elastic Inference accelerator. Learn more about creating an IAM role to use with Elastic Inference.
CPU options
Specify CPU options
Shutdown behavior
Stop
Enable termination protection
Protect against accidental termination
Monitoring
Enable CloudWatch detailed monitoring
Additional charges apply
Cancel
Previous
Review and Launch
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Feedback
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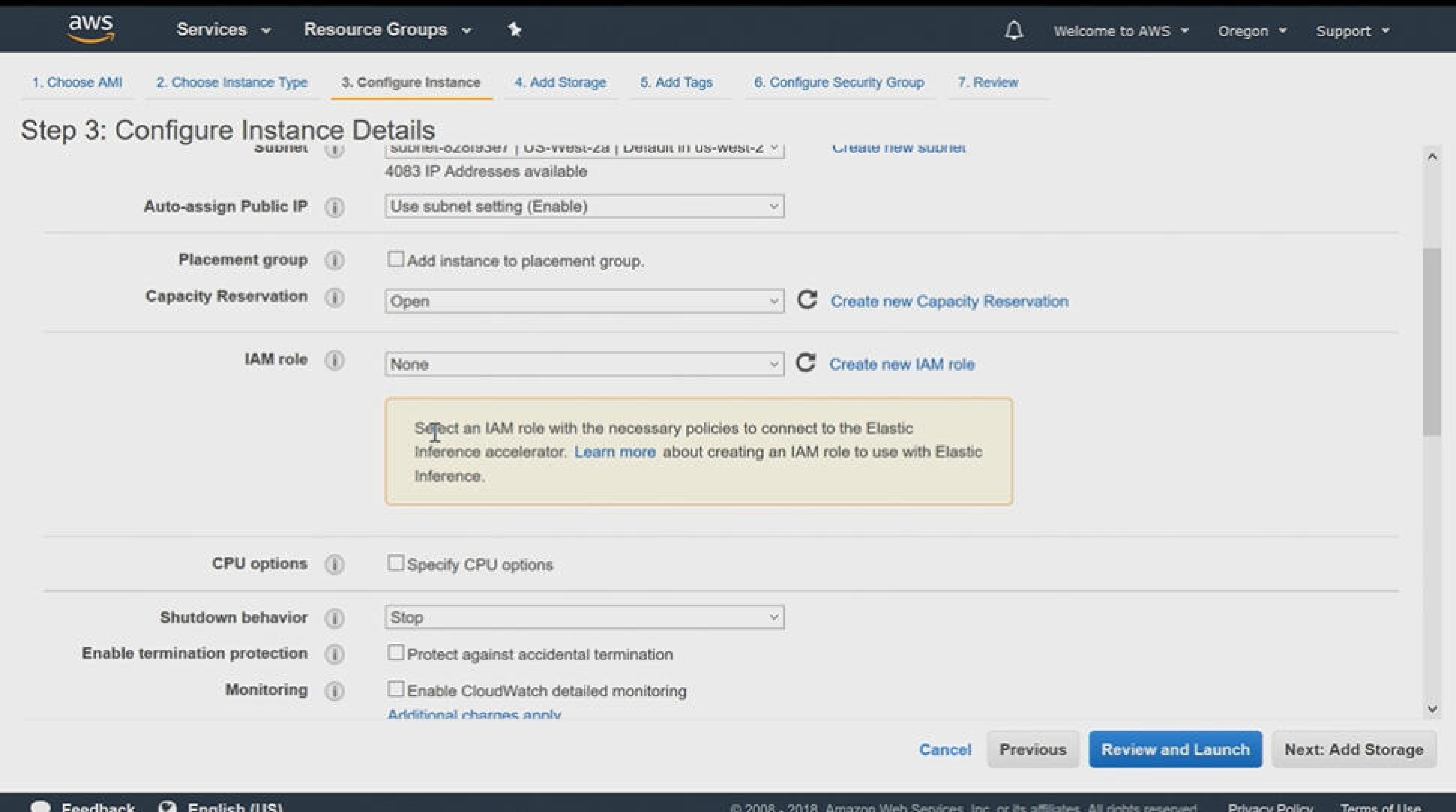

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4. Add Storage
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Auto-assign Public IP
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Create new IAM role
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CPU options
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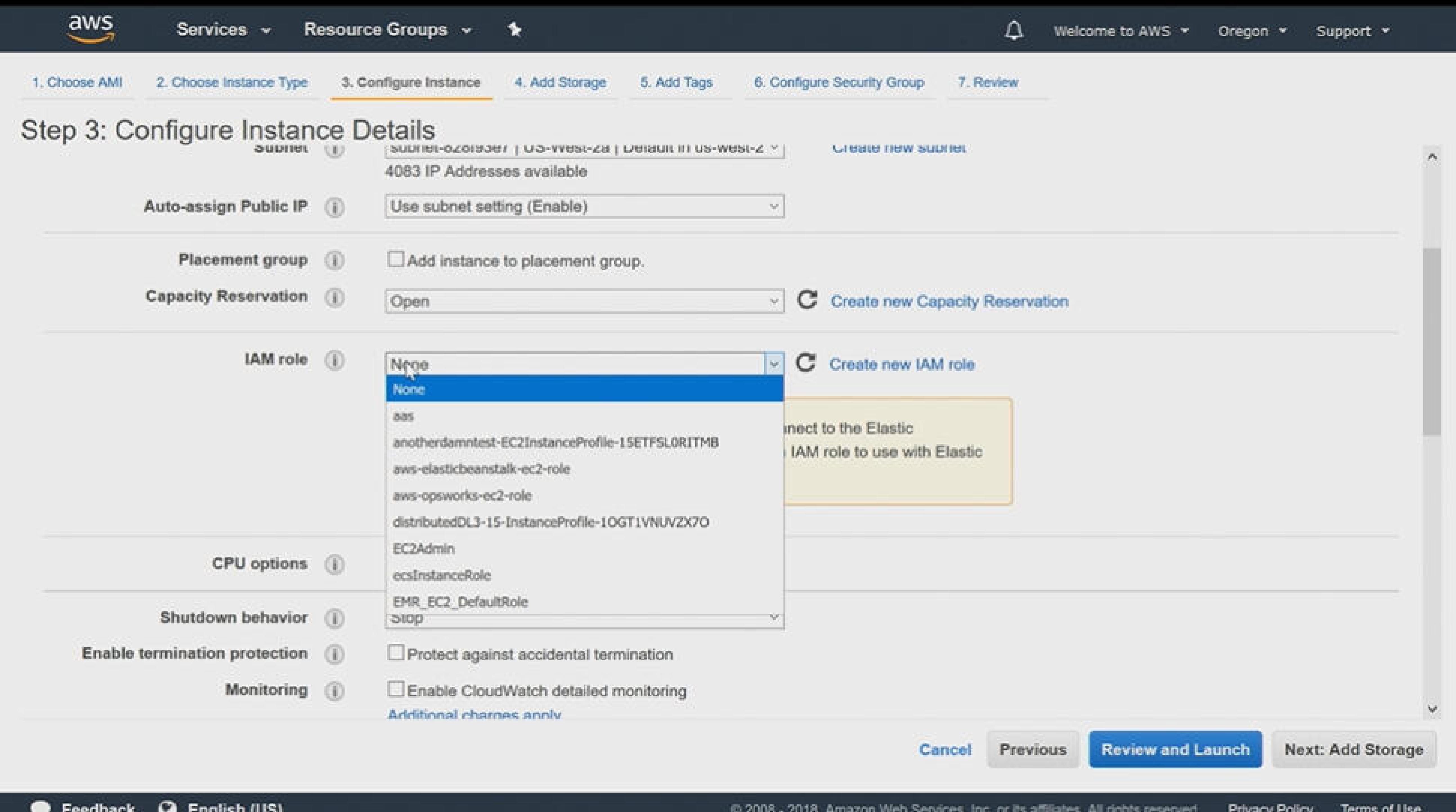
Shutdown behavior
Stop
Enable termination protection
Protect against accidental termination
Monitoring
Enable CloudWatch detailed monitoring
Cancel
Previous
Review and Launch
Next: Add Storage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Open
Create new Capacity Reservation
IAM role
None
Create new IAM role
None
aas
anotherdamntest-EC2InstanceProfile-15ETFSL0RITMB
aws-elasticbeanstalk-ec2-role
aws-opsworks-ec2-role
distributedDL3-15-InstanceProfile-1OGT1VNUVZX7O
EC2Admin
ecsInstanceRole
EMR_EC2_DefaultRole
nect to the Elastic
IAM role to use with Elastic
CPU options
Shutdown behavior
Enable termination protection
Protect against accidental termination
Monitoring
Enable CloudWatch detailed monitoring
Cancel
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aws Services Resource Groups Welcome to AWS Oregon Support

1. Choose AMI 2. Choose Instance Type 3. Configure Instance 4. Add Storage 5. Add Tags 6. Configure Security Group 7. Review

Step 7: Review Instance Launch

Please review your instance launch details. You can go back to edit changes for each section. Click **Launch** to assign a key pair to your instance and complete the launch process.

Your instance configuration is not eligible for the free usage tier

To launch an instance that's eligible for the free usage tier, check your AMI selection, instance type, configuration options, or storage devices. Learn more about free usage tier eligibility and usage restrictions.

Don't show me this again

AMI Details

Edit AMI

Deep Learning AMI (Amazon Linux) Version 18.0 - ami-0454f6c5e35766c6e

With latest deep learning frameworks pre-installed: MXNet, TensorFlow, PyTorch, Keras, Chainer, Caffe/2, Theano & CNTK, configured with NVIDIA CUDA, cuDNN, NCCL & Intel MKL-DNN. For a fully managed experience, check: https://aws.amazon.com/sagemaker

Root Device Type: ebs Virtualization type: hvm

Instance Type

Edit instance type

Instance Type	ECUs	vCPUs	Memory (GiB)	Instance Storage (GB)	EBS-Optimized Available	Network Performance
m5.large	10	2	8	EBS only	Yes	Up to 10 Gigabit

Security Groups

Edit security groups

Cancel Previous Launch

Feedback English (US)

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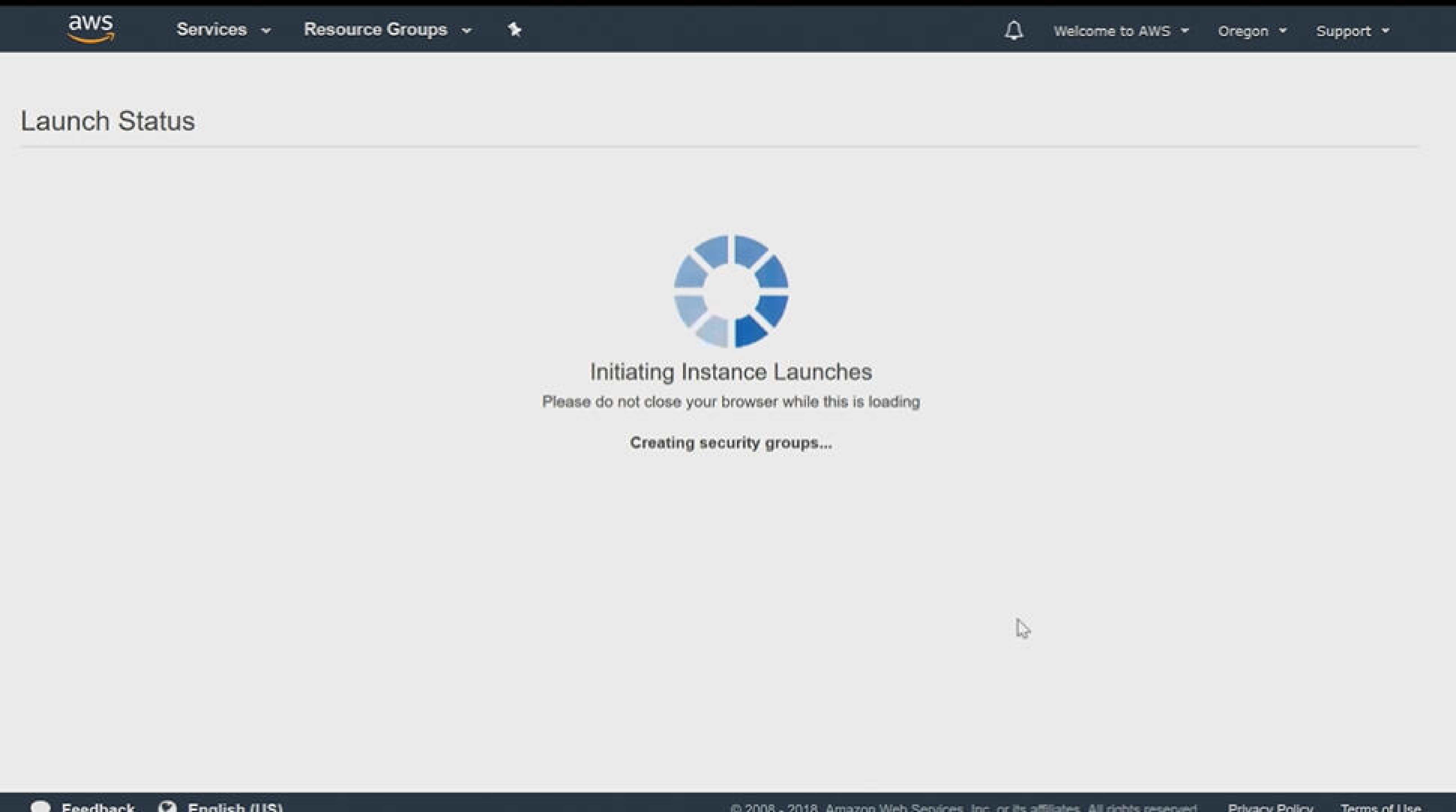
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Launch Status
Initiating Instance Launches
Please do not close your browser while this is loading
Creating security groups...
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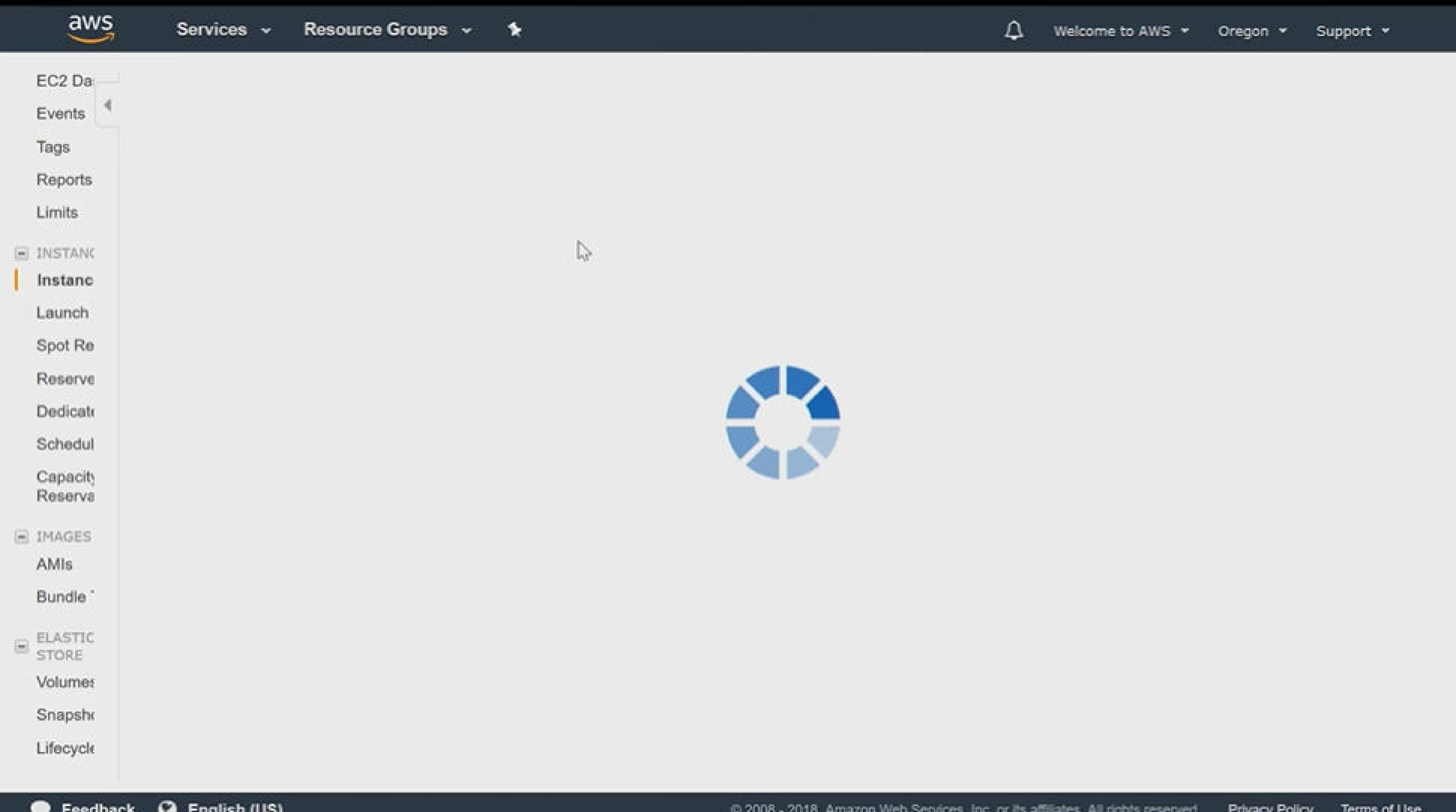
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Reserve
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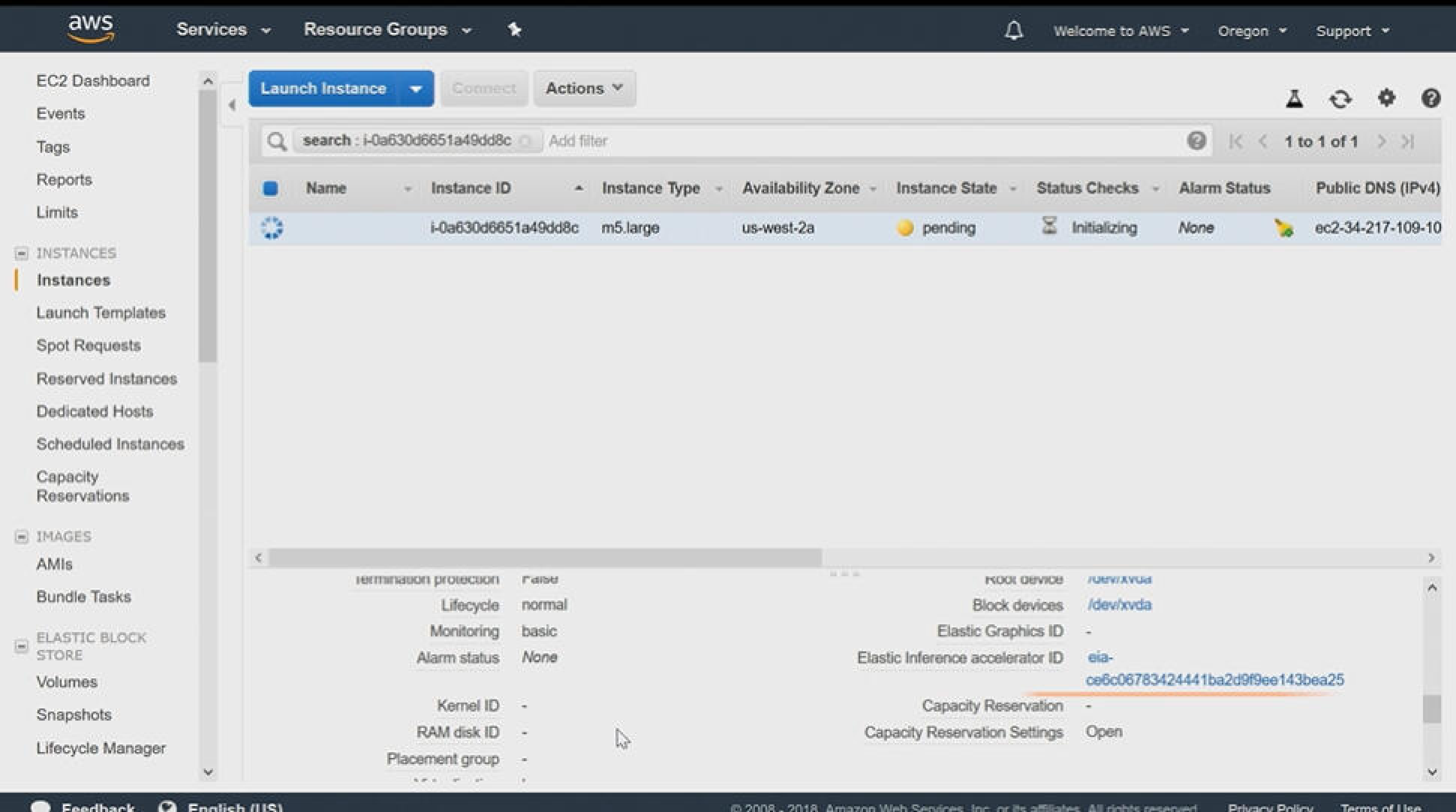

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Dedicated Hosts
Scheduled Instances
Capacity Reservations
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Bundle Tasks
ELASTIC BLOCK STORE
Volumes
Snapshots
Lifecycle Manager
Launch Instance
Connect
Actions
search : i-0a630d6651a49dd8c
Add filter
1 to 1 of 1
Name
Instance ID
Instance Type
Availability Zone
Instance State
Status Checks
Alarm Status
Public DNS (IPv4)
i-0a630d6651a49dd8c
m5.large
us-west-2a
pending
Initializing
None
ec2-34-217-109-10
Lifecycle
normal
Monitoring
basic
Alarm status
None
Kernel ID
-
RAM disk ID
-
Placement group
-
Block devices
/dev/xvda
Elastic Graphics ID
-
Elastic Inference accelerator ID
eia-ce6c06783424441ba2d9f9ee143bea25
Capacity Reservation
-
Capacity Reservation Settings
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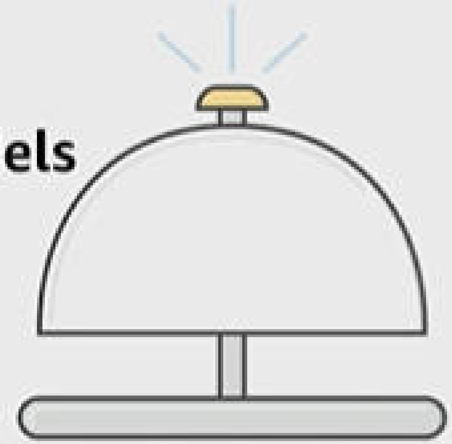
Key Takeaways

aws training and certification

Lowers inference costs by up to 75%

Supports TensorFlow, MXNet & ONNX models

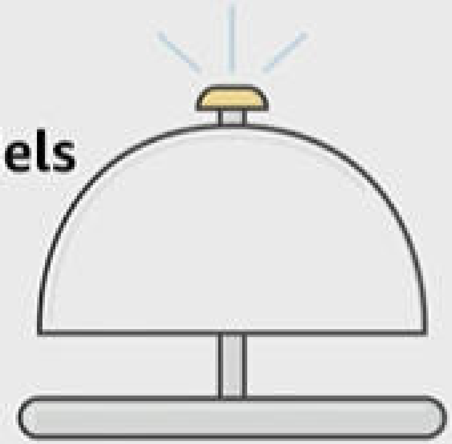


Key Takeaways

aws training and certification

Lowers inference costs by up to 75%

Supports TensorFlow, MXNet & ONNX models

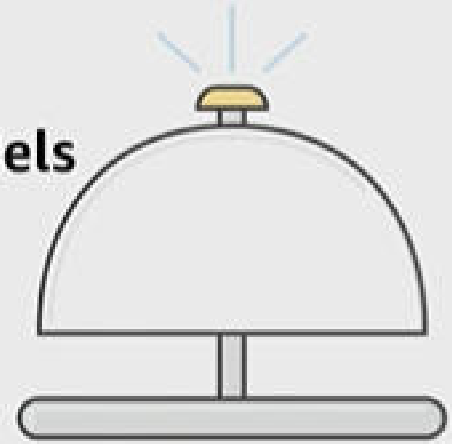


Available to all EC2 instance types.

Key Takeaways

Lowers inference costs by **up to 75%**

Supports **TensorFlow, MXNet & ONNX** models



Available to **all EC2 instance** types.

Key Takeaways

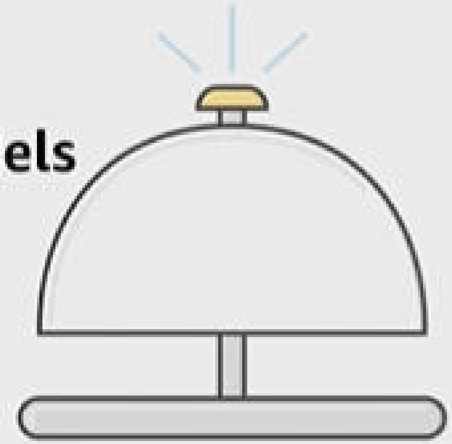
aws training and certification

Lowers inference costs by up to 75%

Supports TensorFlow, MXNet & ONNX models

Available to all EC2 instance types.

Integrated with Amazon SageMaker



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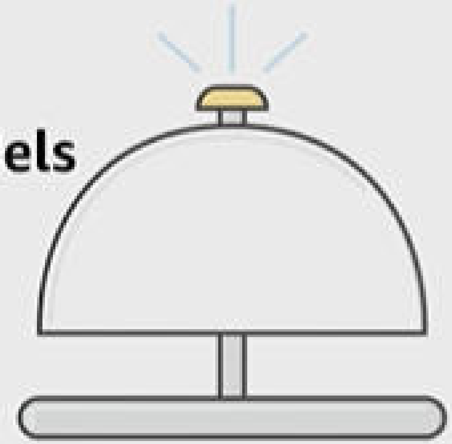

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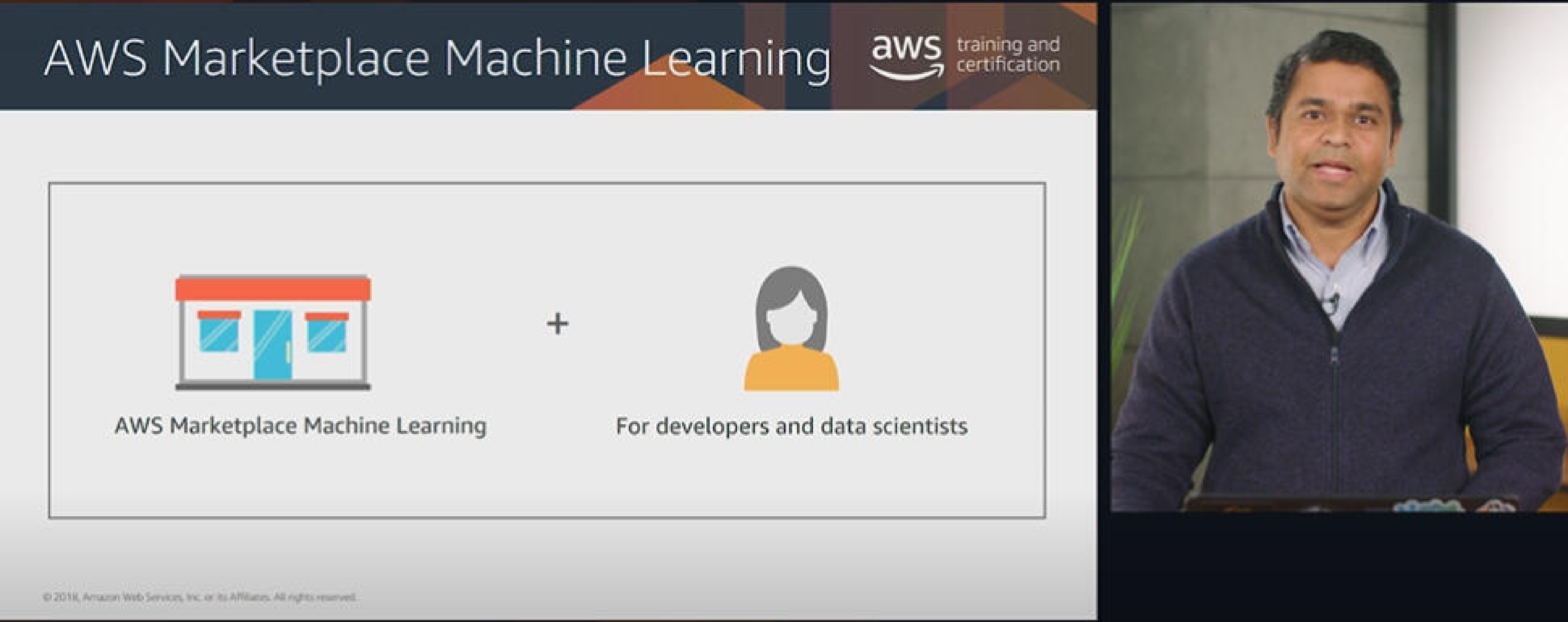
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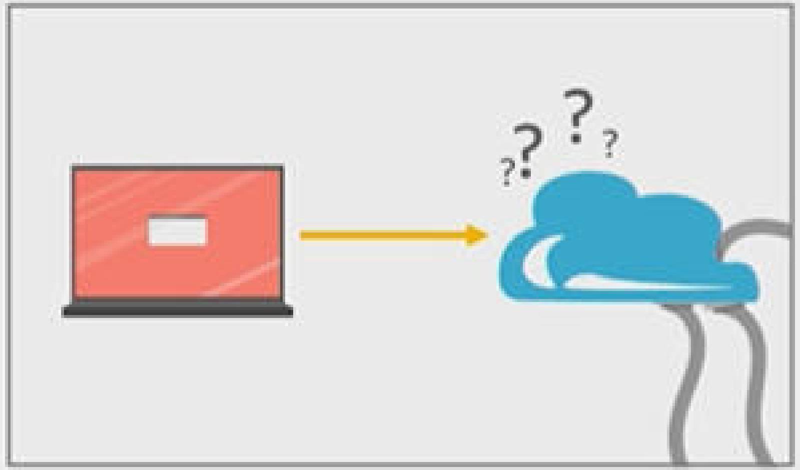
What was the status quo?

Significant time developing

What was the status quo?

Significant time developing



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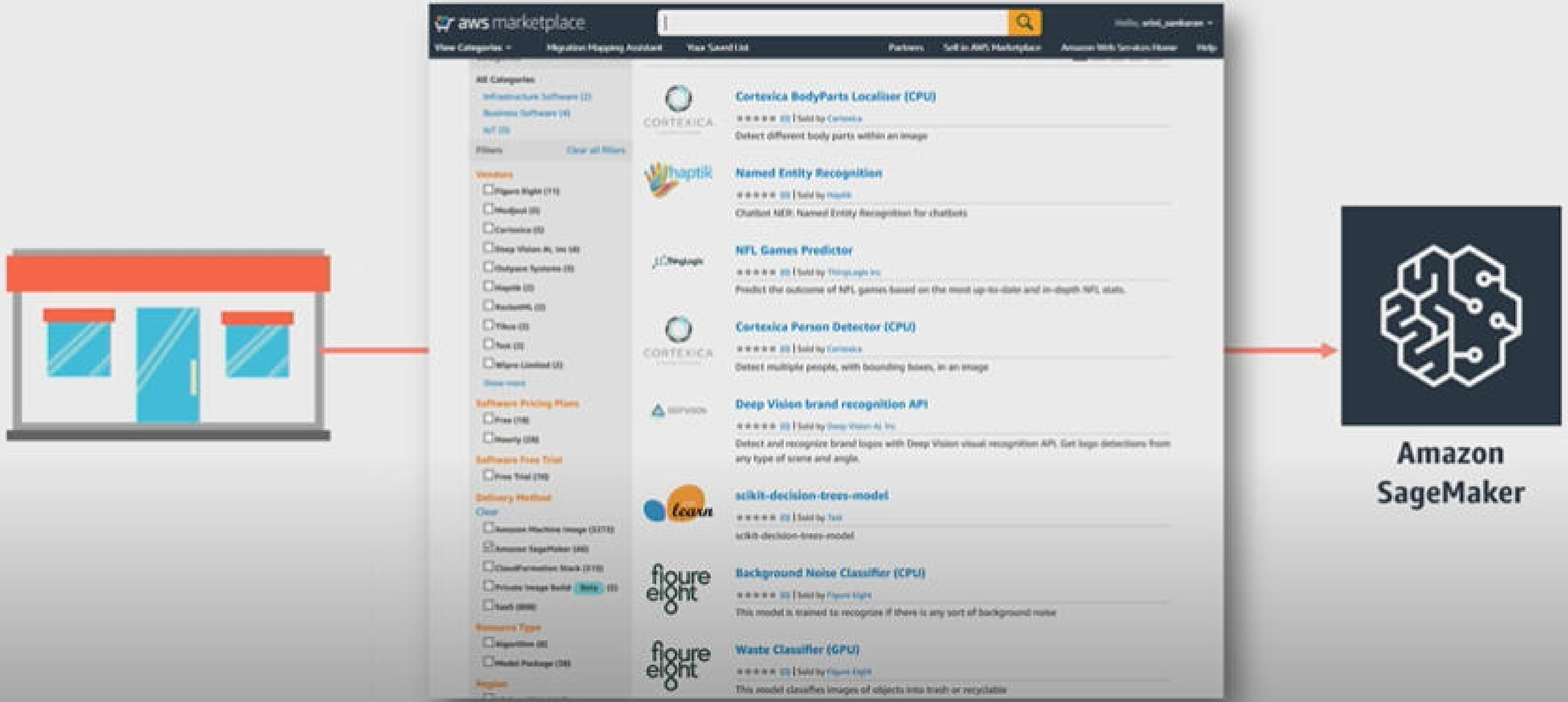

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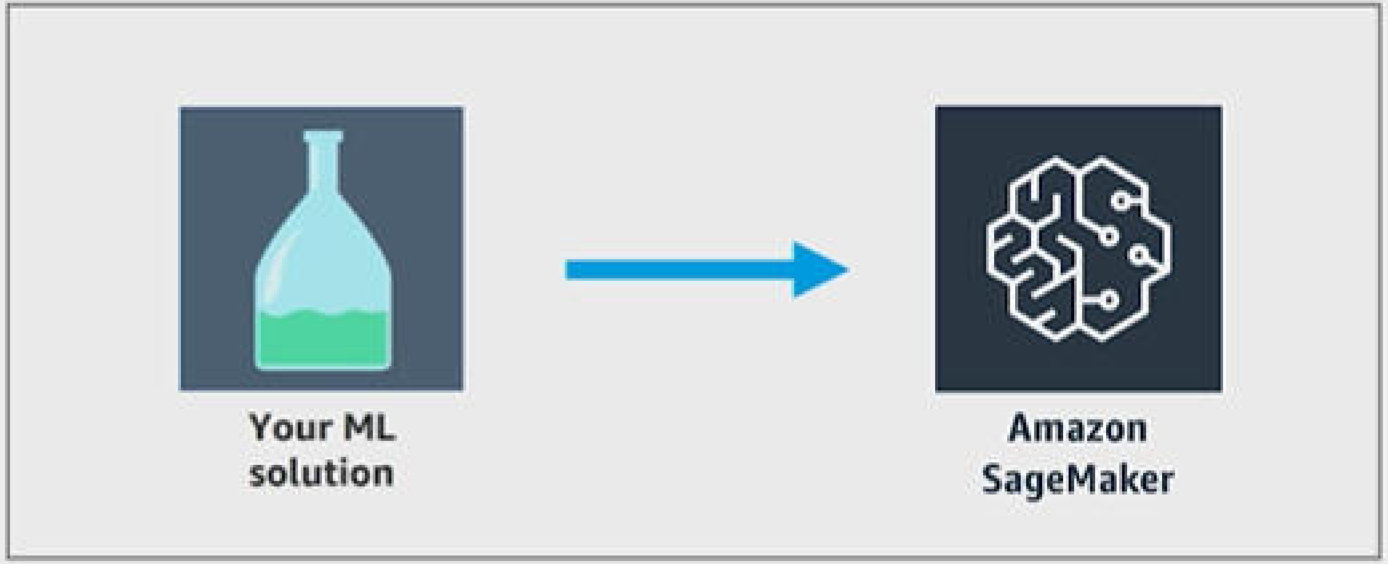

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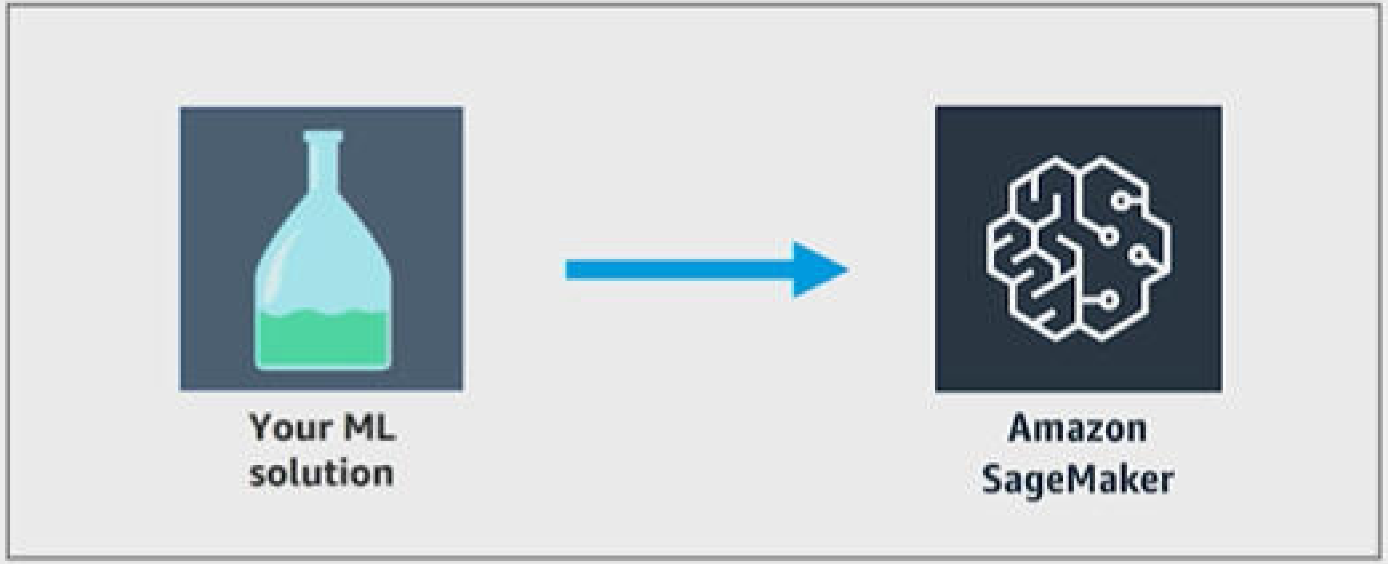

What does this mean for you?

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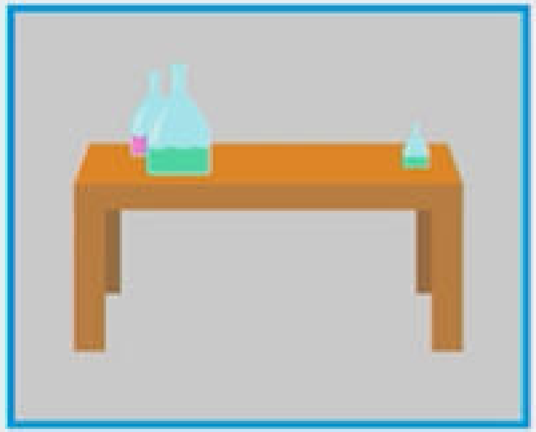

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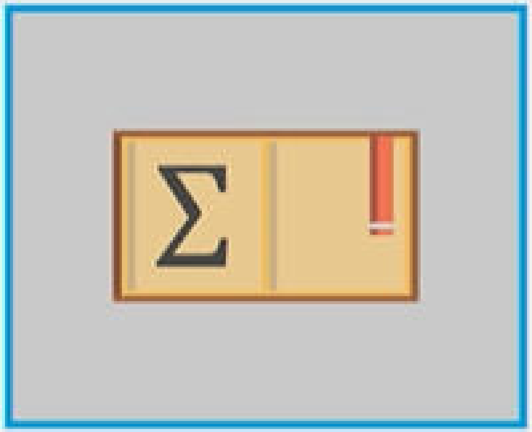
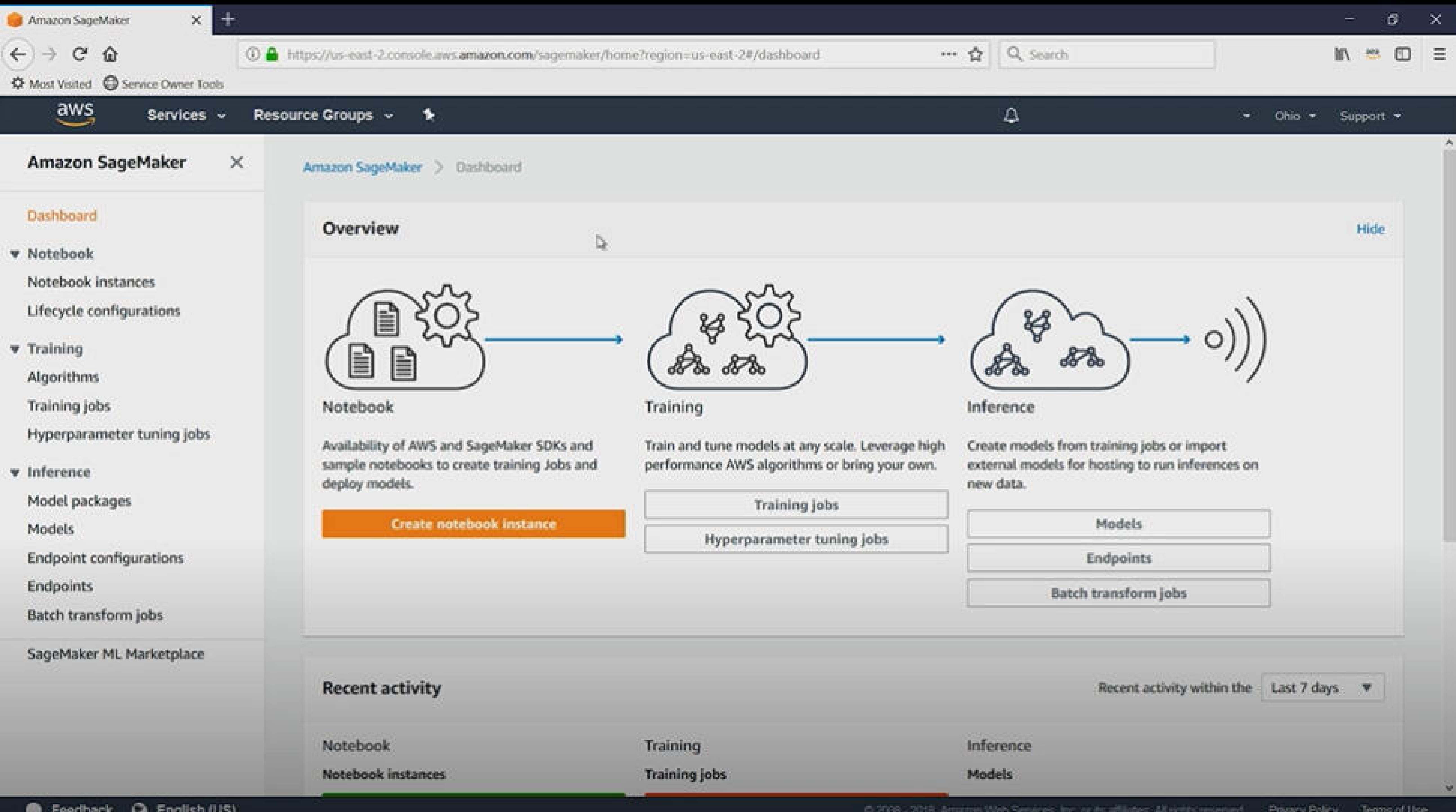


Large catalog of trusted and secure algorithms and models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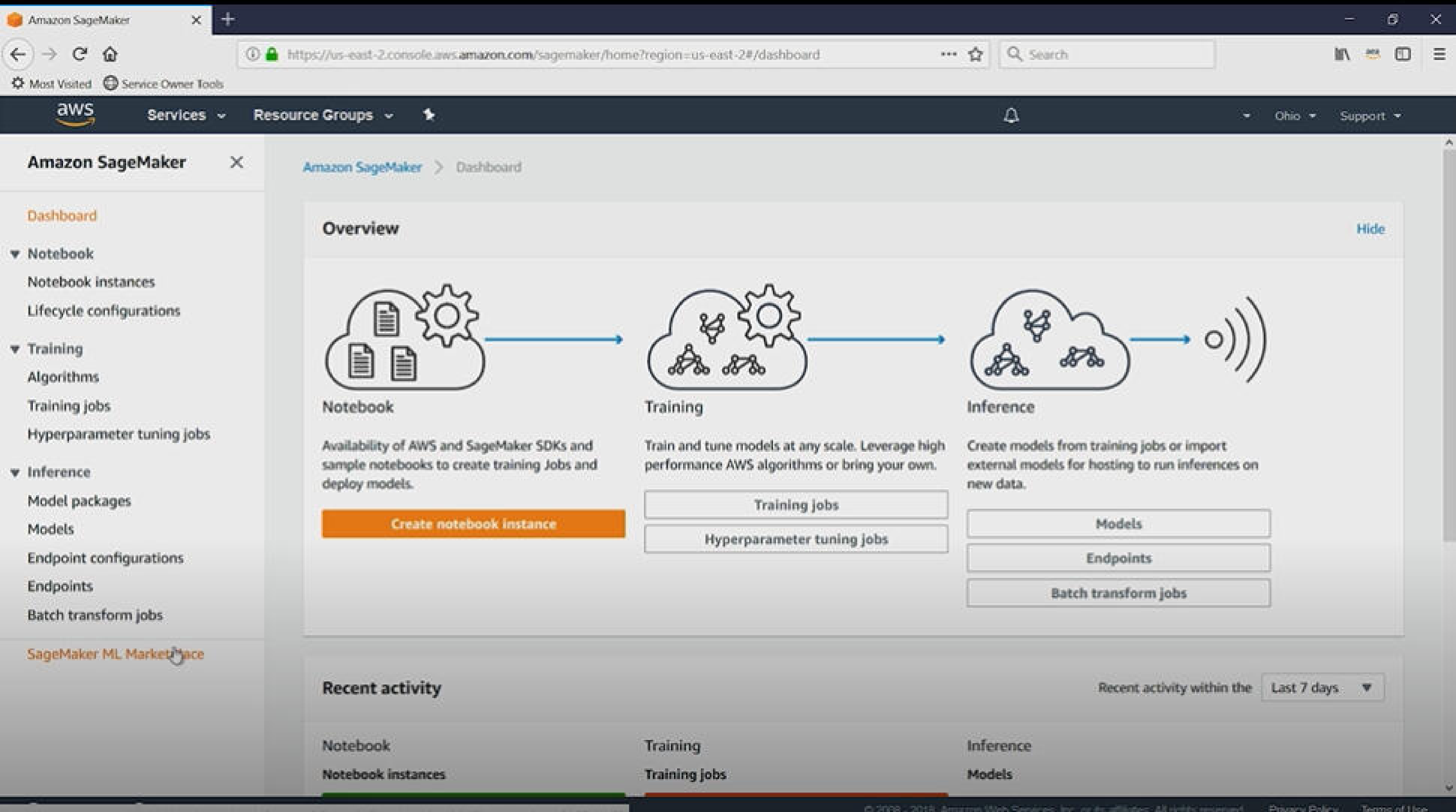
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Detect different body parts within an image

Named Entity Recognition

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Chatbot NER: Named Entity Recognition for chatbots

NFL Games Predictor

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Predict the outcome of NFL games based on the most up-to-date and in-depth NFL stats.

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Detect multiple people, with bounding boxes, in an image

Deep Vision brand recognition API

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Detect and recognize brand logos with Deep Vision visual recognition API. Get logo detections from any type of scene and angle.

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Background Noise Classifier (CPU)

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This model is trained to recognize if there is any sort of background noise

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SageMaker Realtime Inference	**$0.134/host/hr** *running on ml.m5.large*
SageMaker Batch Transform	**$0.134/host/hr** *running on ml.m5.large*

○	ml.m5.12xlarge	$0.5	$3.226	$3.726
○	ml.m5.24xlarge	$0.5	$6.451	$6.951
○	ml.m4.xlarge	$0.5	$0.28	$0.78
○	ml.m4.2xlarge	$0.5	$0.56	$1.06

Usage Information

Fulfillment Methods

Amazon SageMaker

Usage Instructions:
Supported content types are image/jpeg, image/png and image/bmp.

Supported response types are application/json (default), and image/jpeg

After creating an endpoint, the AWS APIs can be used to invoke the model. For, example, you can use the AWS cli:

aws sagemaker-runtime invoke-endpoint --endpoint-name

Additional Resources

Cortexica - AI Solutions for Business

Amazon SageMaker

Amazon SageMaker is a fully-managed platform that enables developers and data scientists to quickly and easily build, train, and deploy machine learning models at any scale. With Amazon SageMaker, all the barriers and complexity that typically slow down developers who want to use machine learning are removed. The service includes

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ml.c5.2xlarge	$1
ml.c5.4xlarge	$1
ml.c5.9xlarge	$1
ml.c5.18xlarge	$1
ml.c4.xlarge	$1

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ml.c5.4xlarge	$1
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ml.c5.9xlarge	$1

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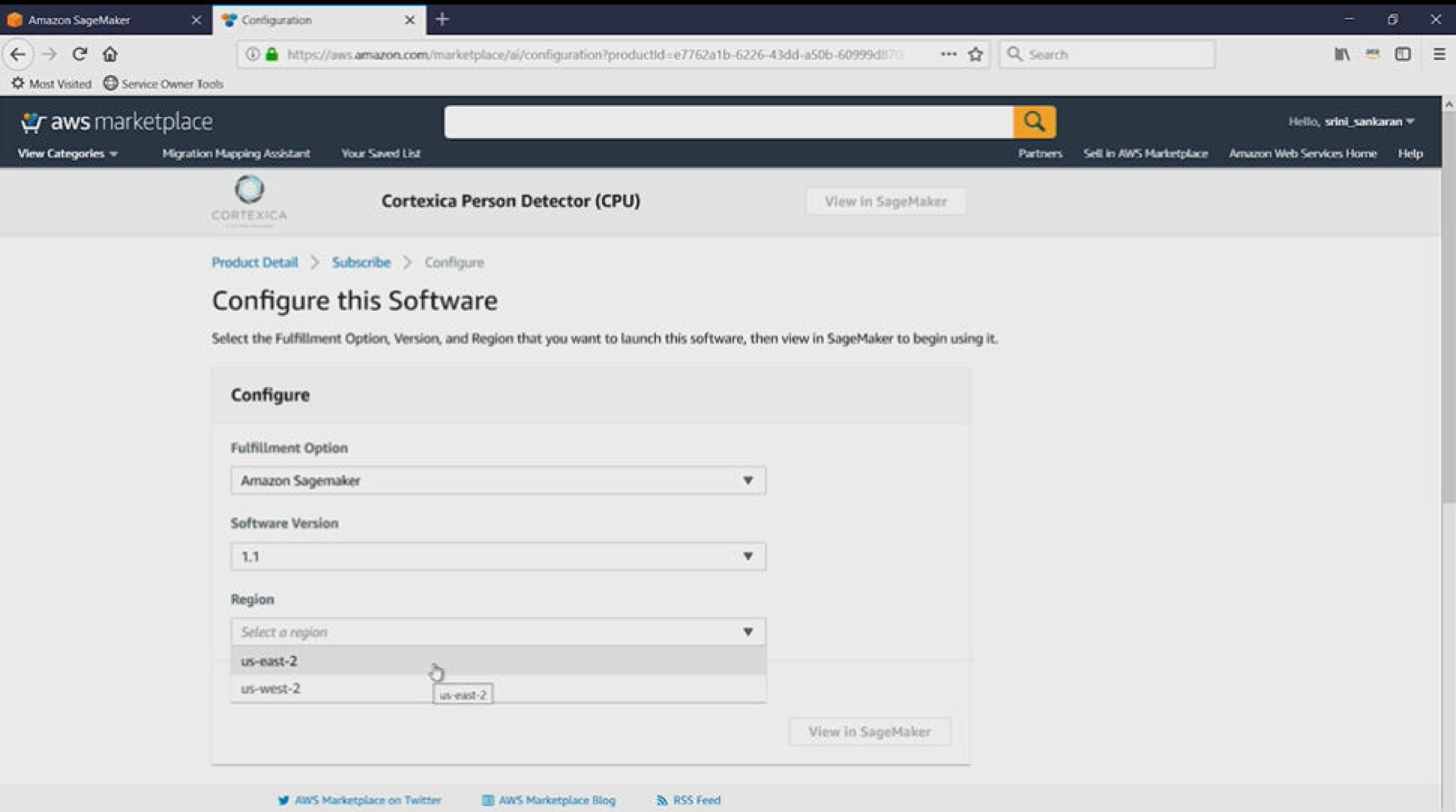
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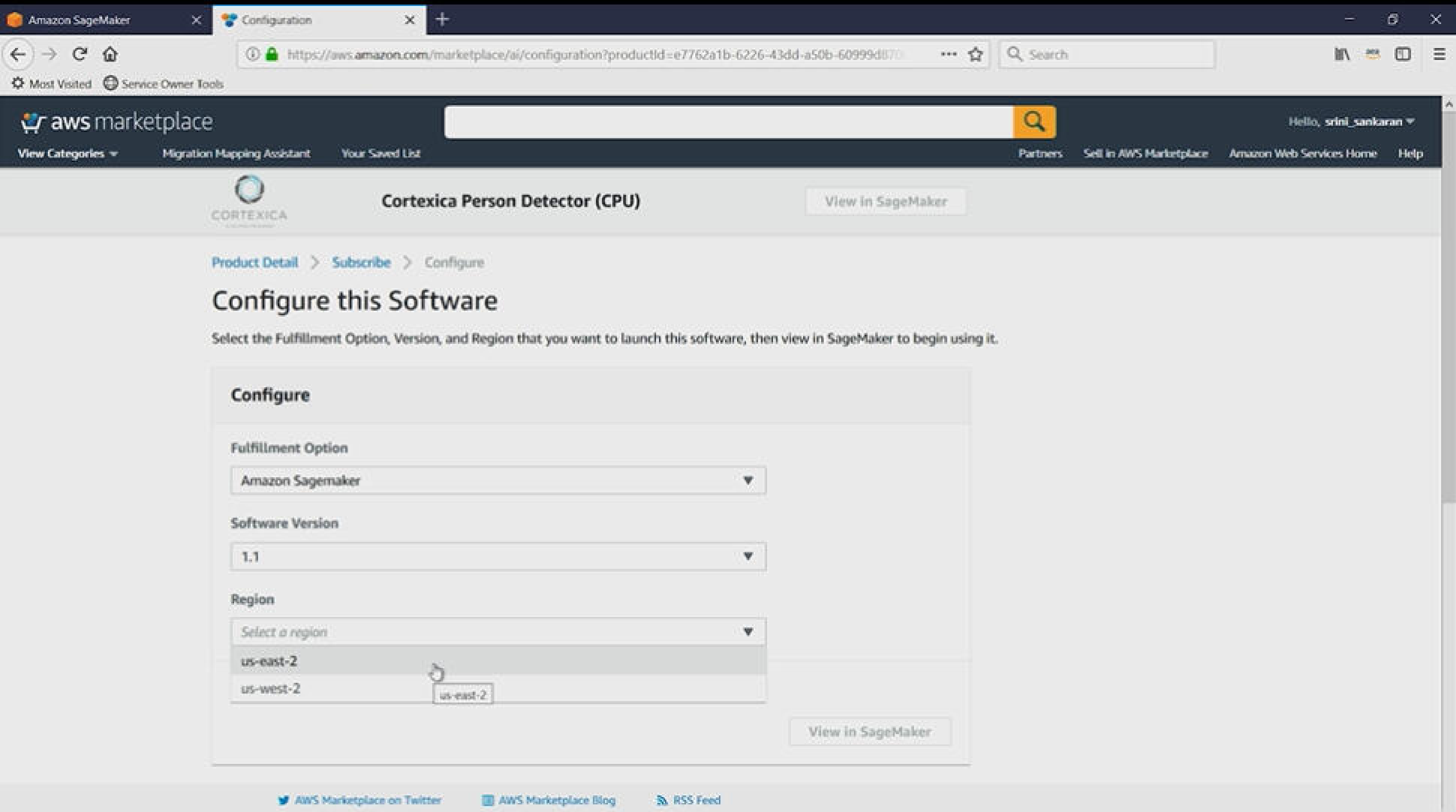
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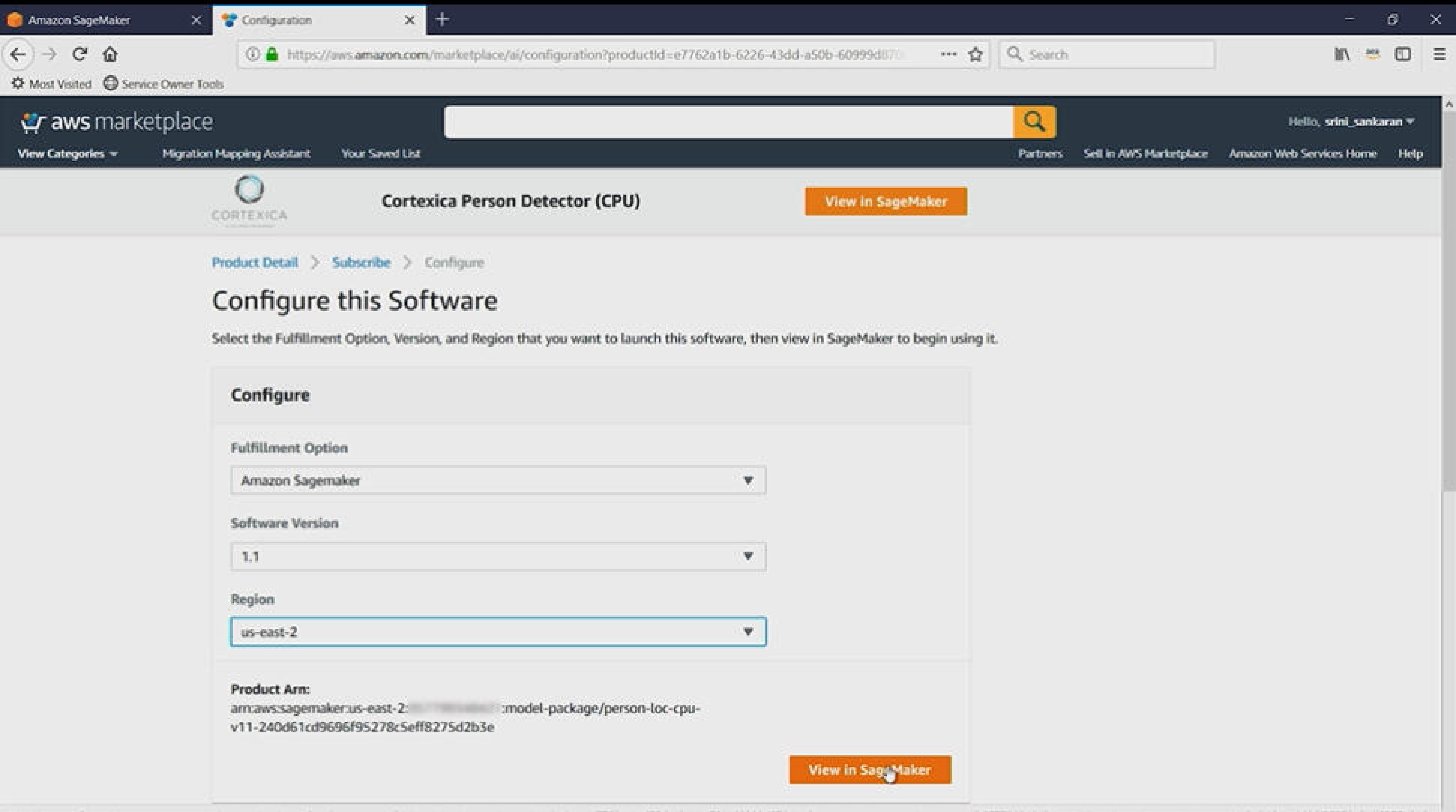
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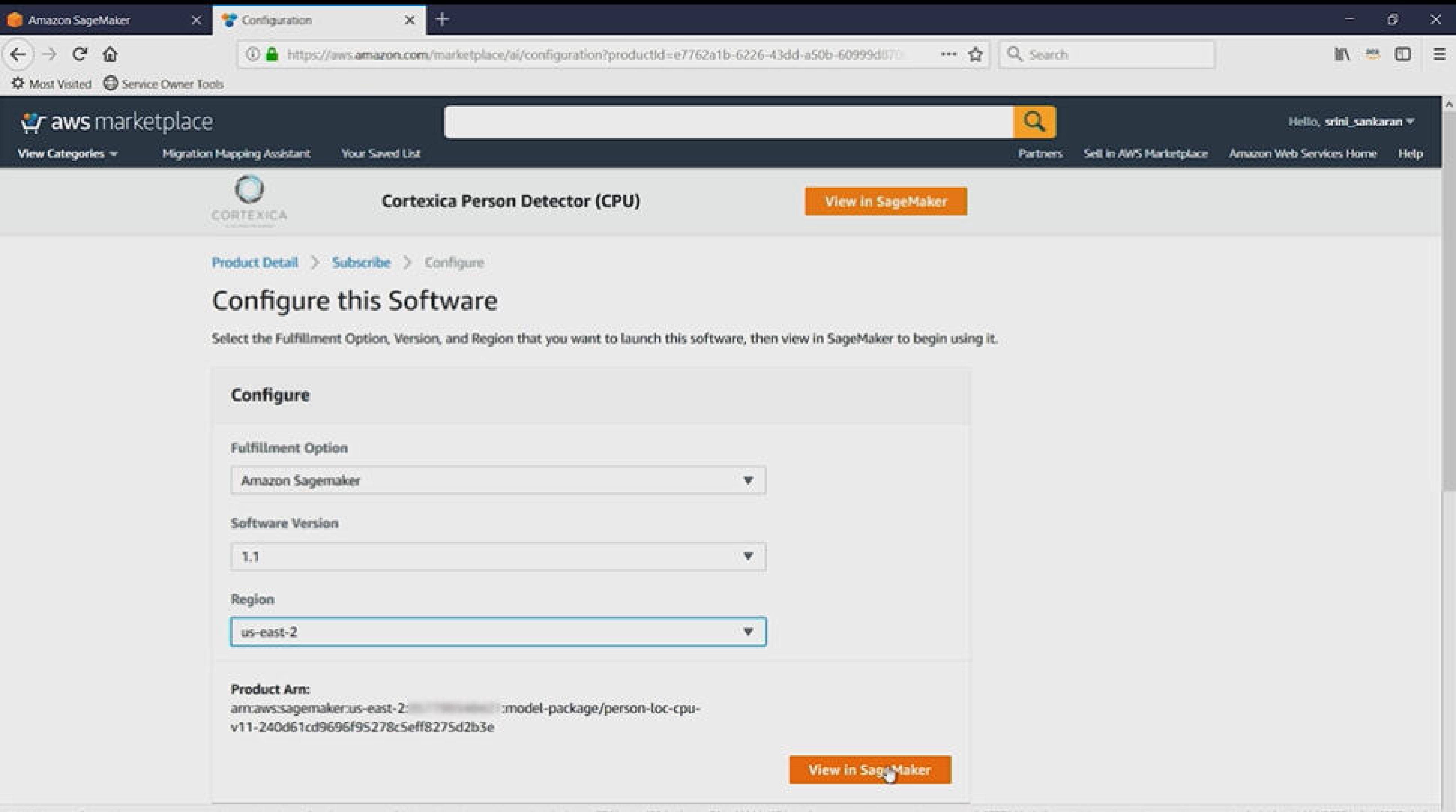
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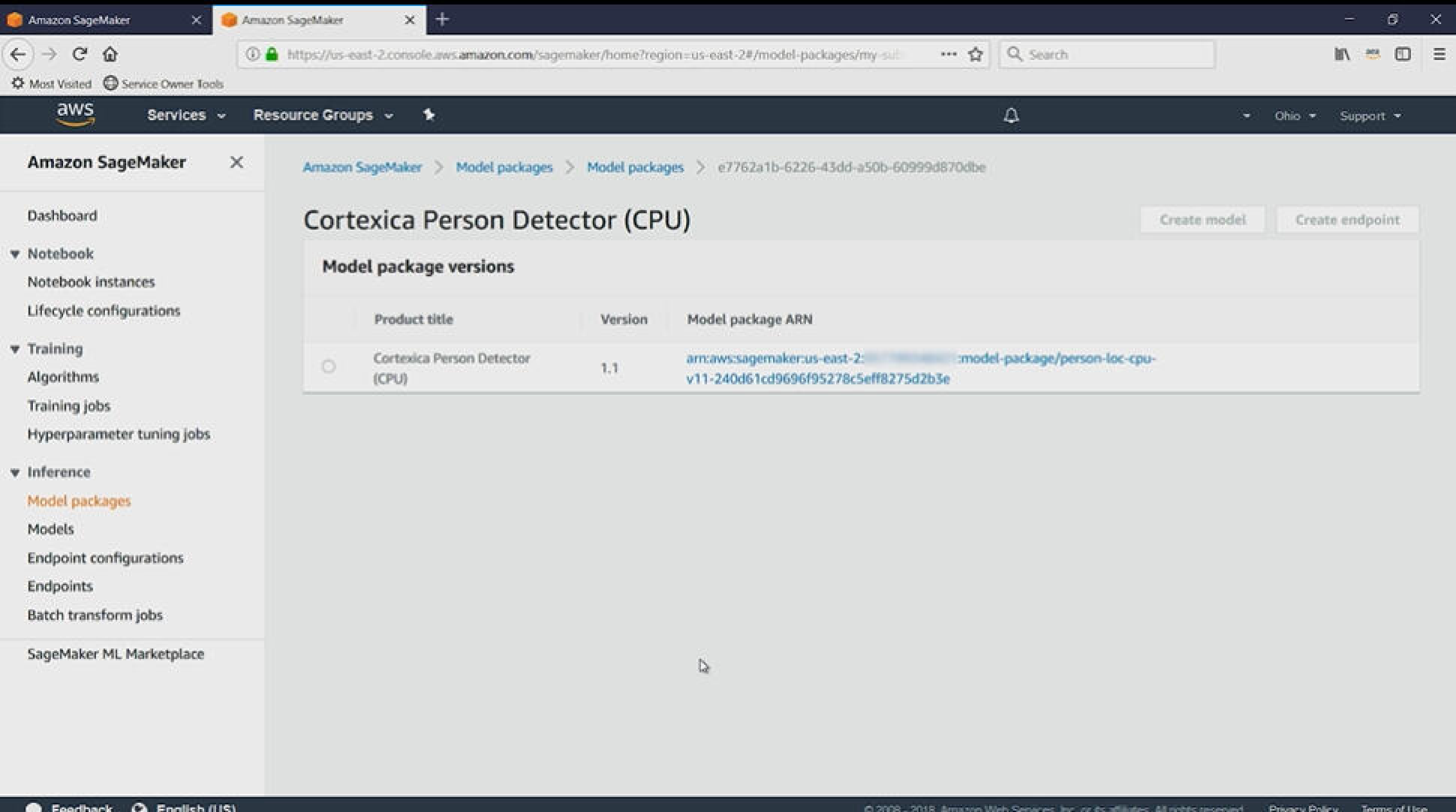
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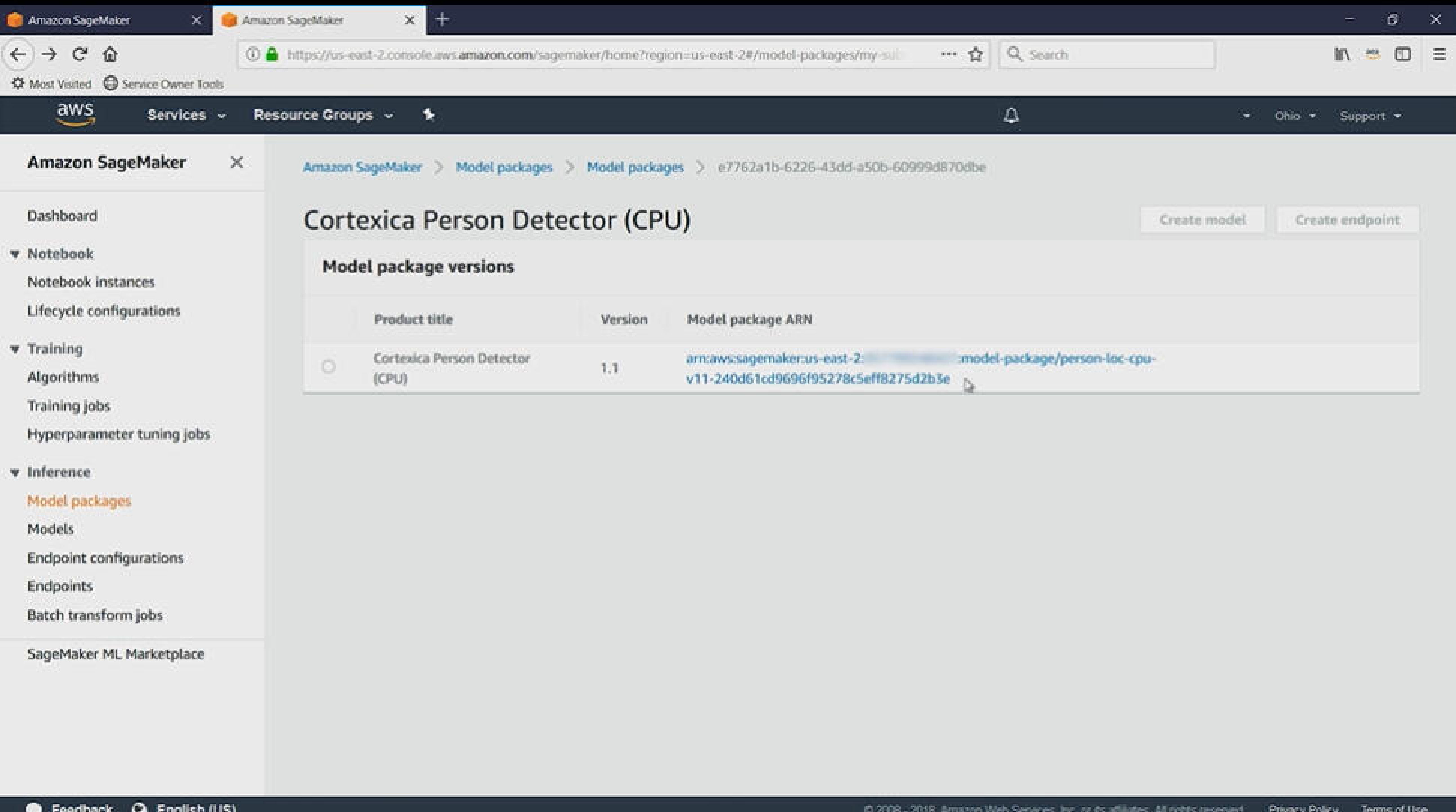
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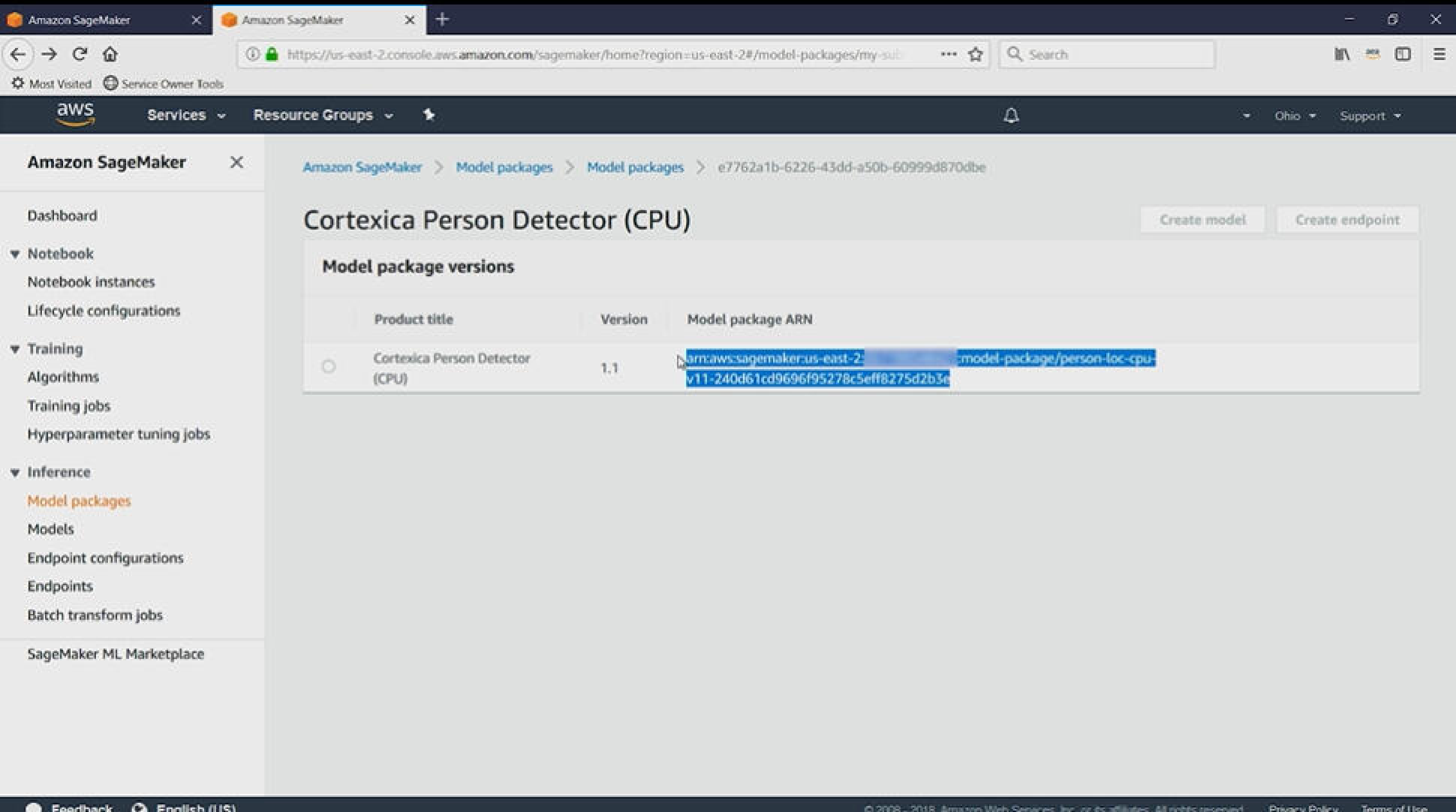
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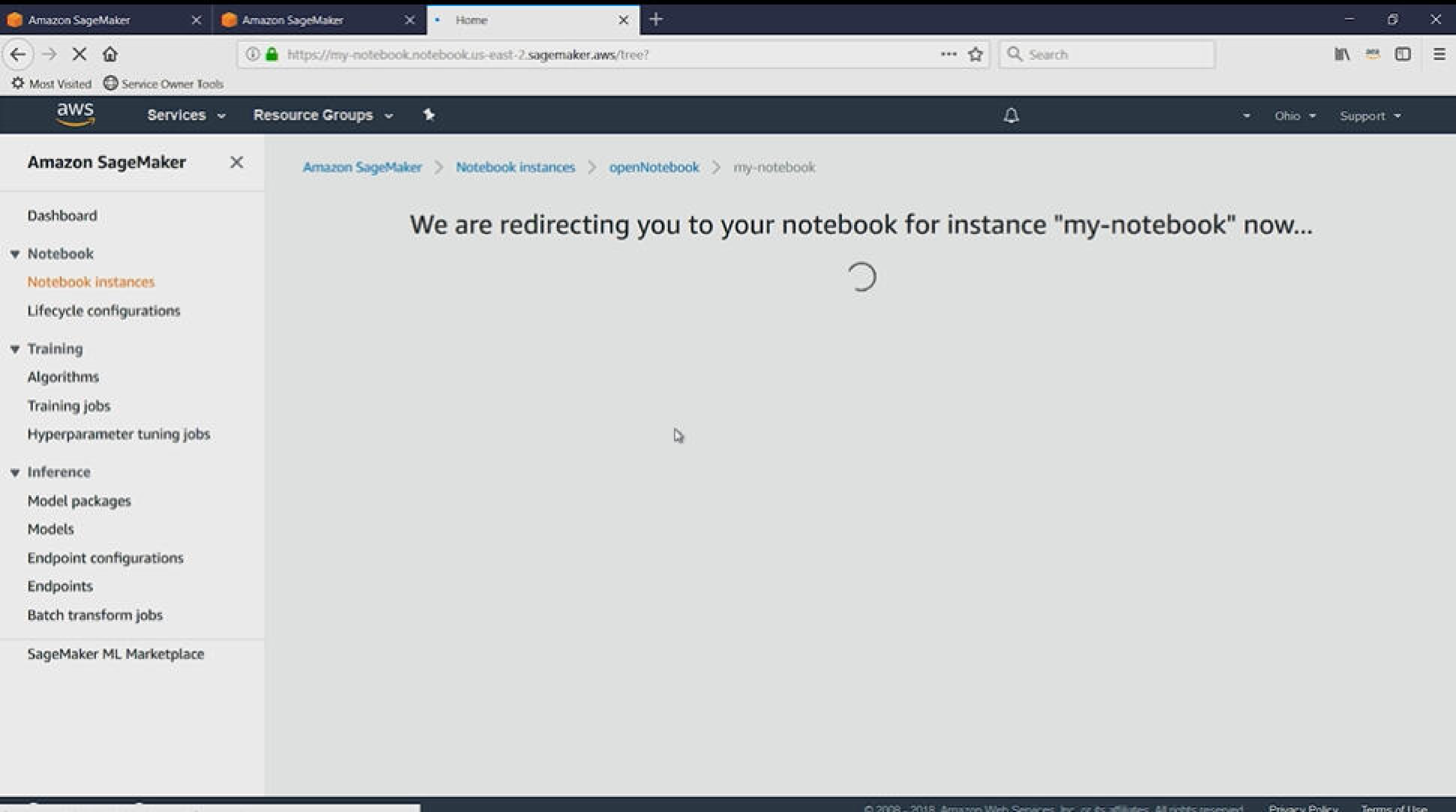
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```
#import necessary libraries
import boto3
import urllib.request
import base64
import json
import os
from sagemaker import get_execution_role
import time
import sagemaker as sagemaker
```

In [ ]:
```
%%sh

aws s3 sync s3://buyer-sm-opt-prm-prvw-1022 ./
chmod +x ./sdk/install-cli.sh
./sdk/install-cli.sh
```

In [ ]:
```
#Initializing BOTO3 client for Amazon SageMaker Service and Amazon SageMaker Runtime, initialising other variables

timestamp = time.strftime('-%Y-%m-%d-%H-%M-%S', time.gmtime())
runtime = boto3.client('sagemaker-runtime')
sagemakermp = boto3.client('sagemakermp', region_name='us-east-2', endpoint_url="https://sagemaker.us-east-2.amazonaws.c
session = sagemaker.Session()

#Specify model package from which end-point needs to be created
modelPackageName='arn:aws:sagemaker:us-east-2:[illegible]:model-package/person-loc-cpu-v11-240d61cd9696f95278c5eff8275d
bucket='sm-testing-ml'
#sm-testing-ml

role = get_execution_role()
modelName='CortexicaPersonDetector-model'+timestamp
endPointConfigName='CortexicaPD-endpoint-config'+timestamp
endPointName='CortexicaPersonDetector-endpoint'+timestamp
batch_job_name='CortexicaPersonDetector-batch-job'+timestamp
```

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In [ ]:
```
#import necessary libraries
import boto3
import urllib.request
import base64
import json
import os
from sagemaker import get_execution_role
import time
import sagemaker as sagemaker
```

In [ ]:
```
%%sh

aws s3 sync s3://buyer-sm-opt-prm-prvw-1022 ./
chmod +x ./sdk/install-cli.sh
./sdk/install-cli.sh
```

In [ ]:
```
#Initializing BOTO3 client for Amazon SageMaker Service and Amazon SageMaker Runtime, initialising other variables

timestamp = time.strftime('-%Y-%m-%d-%H-%M-%S', time.gmtime())
runtime = boto3.client('sagemaker-runtime')
sagemakermp = boto3.client('sagemakermp', region_name='us-east-2', endpoint_url="https://sagemaker.us-east-2.amazonaws.c
session = sagemaker.Session()

#Specify model package from which end-point needs to be created
modelPackageName='arn:aws:sagemaker:us-east-2:[redacted]:model-package/person-loc-cpu-v11-240d61cd9696f95278c5eff8275d
bucket='sm-testing-ml'
#sm-testing-ml

role = get_execution_role()
modelName='CortexicaPersonDetector-model'+timestamp
endPointConfigName='CortexicaPD-endpoint-config'+timestamp
endPointName='CortexicaPersonDetector-endpoint'+timestamp
batch_job_name='CortexicaPersonDetector-batch-job'+timestamp
```

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Run | Code

In [ ]:

```python
#import necessary libraries
import boto3
import urllib.request
import base64
import json
import os
from sagemaker import get_execution_role
import time
import sagemaker as sagemaker
```

In [ ]:

```
%%sh

aws s3 sync s3://buyer-sm-opt-prm-prvw-1022 ./
chmod +x ./sdk/install-cli.sh
./sdk/install-cli.sh
```

In [ ]:

```python
#Initializing BOTO3 client for Amazon SageMaker Service and Amazon SageMaker Runtime, initialising other variables

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runtime = boto3.client('sagemaker-runtime')
sagemakermp = boto3.client('sagemakermp', region_name='us-east-2', endpoint_url="https://sagemaker.us-east-2.amazonaws.c
session = sagemaker.Session()

#Specify model package from which end-point needs to be created
modelPackageName='arn:aws:sagemaker:us-east-2:[redacted]:model-package/person-loc-cpu-v11-240d61cd9696f95278c5eff8275d
bucket='sm-testing-ml'
#sm-testing-ml

role = get_execution_role()
modelName='CortexicaPersonDetector-model'+timestamp
endPointConfigName='CortexicaPD-endpoint-config'+timestamp
endPointName='CortexicaPersonDetector-endpoint'+timestamp
batch_job_name='CortexicaPersonDetector-batch-job'+timestamp
```

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Run   Code

In [ ]:
```python
#import necessary libraries
import boto3
import urllib.request
import base64
import json
import os
from sagemaker import get_execution_role
import time
import sagemaker as sagemaker
```

In [ ]:
```
%%sh

aws s3 sync s3://buyer-sm-opt-prm-prvw-1022 ./
chmod +x ./sdk/install-cli.sh
./sdk/install-cli.sh
```

In [ ]:
```python
#Initializing BOTO3 client for Amazon SageMaker Service and Amazon SageMaker Runtime, initialising other variables

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runtime = boto3.client('sagemaker-runtime')
sagemakermp = boto3.client('sagemakermp', region_name='us-east-2', endpoint_url="https://sagemaker.us-east-2.amazonaws.c
session = sagemaker.Session()

#Specify model package from which end-point needs to be created
modelPackageName='arn:aws:sagemaker:us-east-2:[illegible]:model-package/person-loc-cpu-v11-240d61cd9696f95278c5eff8275d
bucket='sm-testing-ml'
#sm-testing-ml

role = get_execution_role()
modelName='CortexicaPersonDetector-model'+timestamp
endPointConfigName='CortexicaPD-endpoint-config'+timestamp
endPointName='CortexicaPersonDetector-endpoint'+timestamp
batch_job_name='CortexicaPersonDetector-batch-job'+timestamp
```

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Run | Code

In [1]:
```
#import necessary libraries
import boto3
import urllib.request
import base64
import json
import os
from sagemaker import get_execution_role
import time
import sagemaker as sagemaker
```

In [ ]:
```
%%sh

aws s3 sync s3://buyer-sm-opt-prm-prvw-1022 ./
chmod +x ./sdk/install-cli.sh
./sdk/install-cli.sh
```

In [ ]:
```
#Initializing BOTO3 client for Amazon SageMaker Service and Amazon SageMaker Runtime, initialising other variables

timestamp = time.strftime('-%Y-%m-%d-%H-%M-%S', time.gmtime())
runtime = boto3.client('sagemaker-runtime')
sagemakermp = boto3.client('sagemakermp', region_name='us-east-2', endpoint_url="https://sagemaker.us-east-2.amazonaws.c
session = sagemaker.Session()

#Specify model package from which end-point needs to be created
modelPackageName='arn:aws:sagemaker:us-east-2:[redacted]:model-package/person-loc-cpu-v11-240d61cd9696f95278c5eff8275d
bucket='sm-testing-ml'
#sm-testing-ml

role = get_execution_role()
modelName='CortexicaPersonDetector-model'+timestamp
endPointConfigName='CortexicaPD-endpoint-config'+timestamp
endPointName='CortexicaPersonDetector-endpoint'+timestamp
batch_job_name='CortexicaPersonDetector-batch-job'+timestamp
```

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Run Code

```
import json
import os
from sagemaker import get_execution_role
import time
import sagemaker as sagemaker
```

In [2]:

```
%%sh

aws s3 sync s3://buyer-sm-opt-prm-prvw-1022 ./
chmod +x ./sdk/install-cli.sh
./sdk/install-cli.sh
```

```
SageMaker with Marketplace features is now installed to use from boto3 and AWS CLI
```

```
+ aws configure add-model --service-model file:///home/ec2-user/SageMaker/sdk/sagemaker-2017-07-24.normal.json --serv
ice-name sagemakermp
+ echo 'SageMaker with Marketplace features is now installed to use from boto3 and AWS CLI'
```

In [ ]:

```
#Initializing BOTO3 client for Amazon SageMaker Service and Amazon SageMaker Runtime, initializing other variables

timestamp = time.strftime('-%Y-%m-%d-%H-%M-%S', time.gmtime())
runtime = boto3.client('sagemaker-runtime')
sagemakermp = boto3.client('sagemakermp', region_name='us-east-2', endpoint_url="https://sagemaker.us-east-2.amazonaws.c
session = sagemaker.Session()

#Specify model package from which end-point needs to be created
modelPackageName='arn:aws:sagemaker:us-east-2:[illegible]:model-package/person-loc-cpu-v11-240d61cd9696f95278c5eff8275d
bucket='sm-testing-ml'
#sm-testing-ml

role = get_execution_role()
modelName='CortexicaPersonDetector-model'+timestamp
endPointConfigName='CortexicaPD-endpoint-config'+timestamp
endPointName='CortexicaPersonDetector-endpoint'+timestamp
batch_job_name='CortexicaPersonDetector-batch-job'+timestamp
```

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Run | Code

```
SageMaker with Marketplace features is now installed to use from boto3 and AWS CLI
```

```
+ aws configure add-model --service-model file:///home/ec2-user/SageMaker/sdk/sagemaker-2017-07-24.normal.json --serv
ice-name sagemakermp
+ echo 'SageMaker with Marketplace features is now installed to use from boto3 and AWS CLI'
```

In [ ]:

```
#Initializing BOTO3 client for Amazon SageMaker Service and Amazon SageMaker Runtime, initializing other variables

timestamp = time.strftime('-%Y-%m-%d-%H-%M-%S', time.gmtime())
runtime = boto3.client('sagemaker-runtime')
sagemakermp = boto3.client('sagemakermp', region_name='us-east-2', endpoint_url="https://sagemaker.us-east-2.amazonaws.c
session = sagemaker.Session()

#Specify model package from which end-point needs to be created
modelPackageName='arn:aws:sagemaker:us-east-2:[redacted]:model-package/person-loc-cpu-v11-240d61cd9696f95278c5eff8275d
bucket='sm-testing-ml'
#sm-testing-ml

role = get_execution_role()
modelName='CortexicaPersonDetector-model'+timestamp
endPointConfigName='CortexicaPD-endpoint-config'+timestamp
endPointName='CortexicaPersonDetector-endpoint'+timestamp
batch_job_name='CortexicaPersonDetector-batch-job'+timestamp
```

In [ ]:

```
#First create a model from the model-package

create_model_response = sagemakermp.create_model(
    ModelName=modelName,
    Containers=[
        {
            'ModelPackageName': modelPackageName
        }
    ],
    ExecutionRoleArn=role,
    EnableNetworkIsolation=True
```

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Run | Code

```
+ echo 'SageMaker with Marketplace features is now installed to use from boto3 and AWS CLI'
```

In [3]:

```
#Initializing BOTO3 client for Amazon SageMaker Service and Amazon SageMaker Runtime, initializing other variables

timestamp = time.strftime('-%Y-%m-%d-%H-%M-%S', time.gmtime())
runtime = boto3.client('sagemaker-runtime')
sagemakermp = boto3.client('sagemakermp', region_name='us-east-2', endpoint_url="https://sagemaker.us-east-2.amazonaws.c
session = sagemaker.Session()

#Specify model package from which end-point needs to be created
modelPackageName='arn:aws:sagemaker:us-east-2:[redacted]:model-package/person-loc-cpu-v11-240d61od9696f95278c5eff8275d
bucket='sm-testing-ml'
#sm-testing-ml

role = get_execution_role()
modelName='CortexicaPersonDetector-model'+timestamp
endPointConfigName='CortexicaPD-endpoint-config'+timestamp
endPointName='CortexicaPersonDetector-endpoint'+timestamp
batch_job_name='CortexicaPersonDetector-batch-job'+timestamp
```

In [ ]:

```
#First create a model from the model-package

create_model_response = sagemakermp.create_model(
    ModelName=modelName,
    Containers=[
        {
            'ModelPackageName': modelPackageName
        }
    ],
    ExecutionRoleArn=role,
    EnableNetworkIsolation=True
)
create_model_response
```

In [ ]:

```
#First create an Endpoint configuration
```

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Run | Code

```python
bucket='sm-testing-ml'
#sm-testing-ml

role = get_execution_role()
modelName='CortexicaPersonDetector-model'+timestamp
endPointConfigName='CortexicaPD-endpoint-config'+timestamp
endPointName='CortexicaPersonDetector-endpoint'+timestamp
batch_job_name='CortexicaPersonDetector-batch-job'+timestamp
```

In [ ]:

```python
#First create a model from the model-package

create_model_response = sagemakermp.create_model(
    ModelName=modelName,
    Containers=[
        {
            'ModelPackageName': modelPackageName
        }
    ],
    ExecutionRoleArn=role,
    EnableNetworkIsolation=True
)
create_model_response
```

In [ ]:

```python
#First create an Endpoint configuration

create_endpoint_config_response = sagemakermp.create_endpoint_config(
    EndpointConfigName=endPointConfigName,
    ProductionVariants=[
        {
            'VariantName': 'default-variant-name',
            'ModelName': modelName,
            'InitialInstanceCount': 1,
            'InstanceType': 'ml.c5.xlarge',
            'InitialVariantWeight': 1
        },
    ],
```

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Run | Code

```
bucket='sm-testing-ml'
#sm-testing-ml

role = get_execution_role()
modelName='CortexicaPersonDetector-model'+timestamp
endPointConfigName='CortexicaPD-endpoint-config'+timestamp
endPointName='CortexicaPersonDetector-endpoint'+timestamp
batch_job_name='CortexicaPersonDetector-batch-job'+timestamp
```

In [ ]:

```
#First create a model from the model-package

create_model_response = sagemakermp.create_model(
    ModelName=modelName,
    Containers=[
        {
            'ModelPackageName': modelPackageName
        }
    ],
    ExecutionRoleArn=role,
    EnableNetworkIsolation=True
)
create_model_response
```

In [ ]:

```
#First create an Endpoint configuration

create_endpoint_config_response = sagemakermp.create_endpoint_config(
    EndpointConfigName=endPointConfigName,
    ProductionVariants=[
        {
            'VariantName': 'default-variant-name',
            'ModelName': modelName,
            'InitialInstanceCount': 1,
            'InstanceType': 'ml.c5.xlarge',
            'InitialVariantWeight': 1
        },
    ],
```

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Run | Code

```
role = get_execution_role()
modelName='CortexicaPersonDetector-model'+timestamp
endPointConfigName='CortexicaPD-endpoint-config'+timestamp
endPointName='CortexicaPersonDetector-endpoint'+timestamp
batch_job_name='CortexicaPersonDetector-batch-job'+timestamp
```

In [4]:

```
#First create a model from the model-package

create_model_response = sagemakermp.create_model(
    ModelName=modelName,
    Containers=[
        {
            'ModelPackageName': modelPackageName
        }
    ],
    ExecutionRoleArn=role,
    EnableNetworkIsolation=True
)
create_model_response
```

Out[4]:

```
{'ModelArn': 'arn:aws:sagemaker:us-east-2:[illegible]:model/cortexicapersondetector-model-2018-11-07-19-20-02',
 'ResponseMetadata': {'RequestId': '290c6ce2-1513-428f-8727-4b74ac2a3866',
  'HTTPStatusCode': 200,
  'HTTPHeaders': {'x-amzn-requestid': '290c6ce2-1513-428f-8727-4b74ac2a3866',
   'content-type': 'application/x-amz-json-1.1',
   'content-length': '111',
   'date': 'Wed, 07 Nov 2018 19:20:20 GMT'},
  'RetryAttempts': 0}}
```

In [ ]:

```
#First create an Endpoint configuration

create_endpoint_config_response = sagemakermp.create_endpoint_config(
    EndpointConfigName=endPointConfigName,
    ProductionVariants=[
        {
            'VariantName': 'default-variant-name',
```

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```
role = get_execution_role()
modelName='CortexicaPersonDetector-model'+timestamp
endPointConfigName='CortexicaPD-endpoint-config'+timestamp
endPointName='CortexicaPersonDetector-endpoint'+timestamp
batch_job_name='CortexicaPersonDetector-batch-job'+timestamp
```

In [4]:

```
#First create a model from the model-package

create_model_response = sagemakermp.create_model(
    ModelName=modelName,
    Containers=[
        {
            'ModelPackageName': modelPackageName
        }
    ],
    ExecutionRoleArn=role,
    EnableNetworkIsolation=True
)
create_model_response
```

Out[4]:

```
{'ModelArn': 'arn:aws:sagemaker:us-east-2:[redacted]:model/cortexicapersondetector-model-2018-11-07-19-20-02',
 'ResponseMetadata': {'RequestId': '290c6ce2-1513-428f-8727-4b74ac2a3866',
  'HTTPStatusCode': 200,
  'HTTPHeaders': {'x-amzn-requestid': '290c6ce2-1513-428f-8727-4b74ac2a3866',
   'content-type': 'application/x-amz-json-1.1',
   'content-length': '111',
   'date': 'Wed, 07 Nov 2018 19:20:20 GMT'},
  'RetryAttempts': 0}}
```

In [ ]:

```
#First create an Endpoint configuration

create_endpoint_config_response = sagemakermp.create_endpoint_config(
    EndpointConfigName=endPointConfigName,
    ProductionVariants=[
        {
            'VariantName': 'default-variant-name',
```

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Run | Code

```python
    ModelName=modelName,
    Containers=[
        {
            'ModelPackageName': modelPackageName
        }
    ],
    ExecutionRoleArn=role,
    EnableNetworkIsolation=True
)
create_model_response
```

Out[4]:

```
{'ModelArn': 'arn:aws:sagemaker:us-east-2:[illegible]:model/cortexicapersondetector-model-2018-11-07-19-20-02',
 'ResponseMetadata': {'RequestId': '290c6ce2-1513-428f-8727-4b74ac2a3866',
  'HTTPStatusCode': 200,
  'HTTPHeaders': {'x-amzn-requestid': '290c6ce2-1513-428f-8727-4b74ac2a3866',
   'content-type': 'application/x-amz-json-1.1',
   'content-length': '111',
   'date': 'Wed, 07 Nov 2018 19:20:20 GMT'},
  'RetryAttempts': 0}}
```

In [ ]:

```python
#First create an Endpoint configuration

create_endpoint_config_response = sagemakermp.create_endpoint_config(
    EndpointConfigName=endPointConfigName,
    ProductionVariants=[
        {
            'VariantName': 'default-variant-name',
            'ModelName': modelName,
            'InitialInstanceCount': 1,
            'InstanceType': 'ml.c5.xlarge',
            'InitialVariantWeight': 1
        },
    ],
    Tags=[
        {
            'Key': 'costcenter',
            'Value': '115'
```

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Run | Code

```
    ModelName=modelName,
    Containers=[
        {
            'ModelPackageName': modelPackageName
        }
    ],
    ExecutionRoleArn=role,
    EnableNetworkIsolation=True
)
create_model_response
```

Out[4]:


```
{'ModelArn': 'arn:aws:sagemaker:us-east-2:[redacted]:model/cortexicapersondetector-model-2018-11-07-19-20-02',
 'ResponseMetadata': {'RequestId': '290c6ce2-1513-428f-8727-4b74ac2a3866',
  'HTTPStatusCode': 200,
  'HTTPHeaders': {'x-amzn-requestid': '290c6ce2-1513-428f-8727-4b74ac2a3866',
   'content-type': 'application/x-amz-json-1.1',
   'content-length': '111',
   'date': 'Wed, 07 Nov 2018 19:20:20 GMT'},
  'RetryAttempts': 0}}
```


In [ ]:

```
#First create an Endpoint configuration

create_endpoint_config_response = sagemakermp.create_endpoint_config(
    EndpointConfigName=endPointConfigName,
    ProductionVariants=[
        {
            'VariantName': 'default-variant-name',
            'ModelName': modelName,
            'InitialInstanceCount': 1,
            'InstanceType': 'ml.c5.xlarge',
            'InitialVariantWeight': 1
        },
    ],
    Tags=[
        {
            'Key': 'costcenter',
            'Value': '115'
```

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Run | Code

```
'content-type': 'application/x-amz-json-1.1',
'content-length': '111',
'date': 'Wed, 07 Nov 2018 19:20:20 GMT'},
'RetryAttempts': 0}}
```

In [ ]:

```
#First create an Endpoint configuration

create_endpoint_config_response = sagemakermp.create_endpoint_config(
    EndpointConfigName=endPointConfigName,
    ProductionVariants=[
        {
            'VariantName': 'default-variant-name',
            'ModelName': modelName,
            'InitialInstanceCount': 1,
            'InstanceType': 'ml.c5.xlarge',
            'InitialVariantWeight': 1
        },
    ],
    Tags=[
        {
            'Key': 'costcenter',
            'Value': '115'
        }
    ])
create_endpoint_config_response
```

In [ ]:

```
#First create an Endpoint
#endPointName='my-endpoint'+timestamp

create_endpoint_response=sagemakermp.create_endpoint(
    EndpointName=endPointName,
    EndpointConfigName=endPointConfigName,
    Tags=[{
            'Key': 'test-type',
            'Value': 'cortexica-model-testing'
        }])
create_endpoint_response
```

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Run | Code

```
  'content-type': 'application/x-amz-json-1.1',
  'content-length': '111',
  'date': 'Wed, 07 Nov 2018 19:20:20 GMT'},
 'RetryAttempts': 0}}
```

In [5]:

```
#First create an Endpoint configuration

create_endpoint_config_response = sagemakermp.create_endpoint_config(
    EndpointConfigName=endPointConfigName,
    ProductionVariants=[
        {
            'VariantName': 'default-variant-name',
            'ModelName': modelName,
            'InitialInstanceCount': 1,
            'InstanceType': 'ml.c5.xlarge',
            'InitialVariantWeight': 1
        },
    ],
    Tags=[
        {
            'Key': 'costcenter',
            'Value': '115'
        }
    ])
create_endpoint_config_response
```

Out[5]:

```
{'EndpointConfigArn': 'arn:aws:sagemaker:us-east-2:[illegible]:endpoint-config/cortexicapd-endpoint-config-2018-11-0
7-19-20-02',
 'ResponseMetadata': {'RequestId': 'a2be6669-f1d9-4209-bdf6-804d9325fd36',
  'HTTPStatusCode': 200,
  'HTTPHeaders': {'x-amzn-requestid': 'a2be6669-f1d9-4209-bdf6-804d9325fd36',
   'content-type': 'application/x-amz-json-1.1',
   'content-length': '128',
   'date': 'Wed, 07 Nov 2018 19:20:55 GMT'},
  'RetryAttempts': 0}}
```

In [ ]:

```
#First create an Endpoint
```

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Run   Code


```
 'ResponseMetadata': {'RequestId': 'a2be6669-f1d9-4209-bdf6-804d9325fd36',
  'HTTPStatusCode': 200,
  'HTTPHeaders': {'x-amzn-requestid': 'a2be6669-f1d9-4209-bdf6-804d9325fd36',
   'content-type': 'application/x-amz-json-1.1',
   'content-length': '128',
   'date': 'Wed, 07 Nov 2018 19:20:55 GMT'},
  'RetryAttempts': 0}}
```


In [ ]:
```
#First create an Endpoint
#endPointName='my-endpoint'+timestamp

create_endpoint_response=sagemakermp.create_endpoint(
    EndpointName=endPointName,
    EndpointConfigName=endPointConfigName,
    Tags=[{
            'Key': 'test-type',
            'Value': 'cortexica-model-testing'
        }])
create_endpoint_response
```

In [ ]:
```
#specify input image
url='https://www.amazondelivers.jobs/media/16938/culture.jpg'

#url='https://d2908q01vomgb2.cloudfront.net/cb4e5208b4cd87268b208e49452ed6e89a68e0b8/2018/02/08/smallpdf-webteam-1024x76
```

In [ ]:
```
#Download the input image
urllib.request.urlretrieve(url,'input.jpg')
```

In [ ]:
```
#Perform real-time prediction

#endPointName='my-endpoint-2018-11-07-02-10-30'

runtime = boto3.client('sagemaker-runtime')
with open("input.jpg", "rb") as imageFile:
  f = imageFile.read()
```

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Run | Code

```
 'ResponseMetadata': {'RequestId': 'a2be6669-f1d9-4209-bdf6-804d9325fd36',
  'HTTPStatusCode': 200,
  'HTTPHeaders': {'x-amzn-requestid': 'a2be6669-f1d9-4209-bdf6-804d9325fd36',
   'content-type': 'application/x-amz-json-1.1',
   'content-length': '128',
   'date': 'Wed, 07 Nov 2018 19:20:55 GMT'},
  'RetryAttempts': 0}}
```

In [6]:

```
#First create an Endpoint
#endPointName='my-endpoint'+timestamp

create_endpoint_response=sagemakerrmp.create_endpoint(
    EndpointName=endPointName,
    EndpointConfigName=endPointConfigName,
    Tags=[{
            'Key': 'test-type',
            'Value': 'cortexica-model-testing'
        }])
create_endpoint_response
```

Out[6]:

```
{'EndpointArn': 'arn:aws:sagemaker:us-east-2:[redacted]:endpoint/cortexicapersondetector-endpoint-2018-11-07-19-20-02',
 'ResponseMetadata': {'RequestId': '39a3ec54-269a-4870-8c32-c0ce90c0bc04',
  'HTTPStatusCode': 200,
  'HTTPHeaders': {'x-amzn-requestid': '39a3ec54-269a-4870-8c32-c0ce90c0bc04',
   'content-type': 'application/x-amz-json-1.1',
   'content-length': '120',
   'date': 'Wed, 07 Nov 2018 19:21:09 GMT'},
  'RetryAttempts': 0}}
```

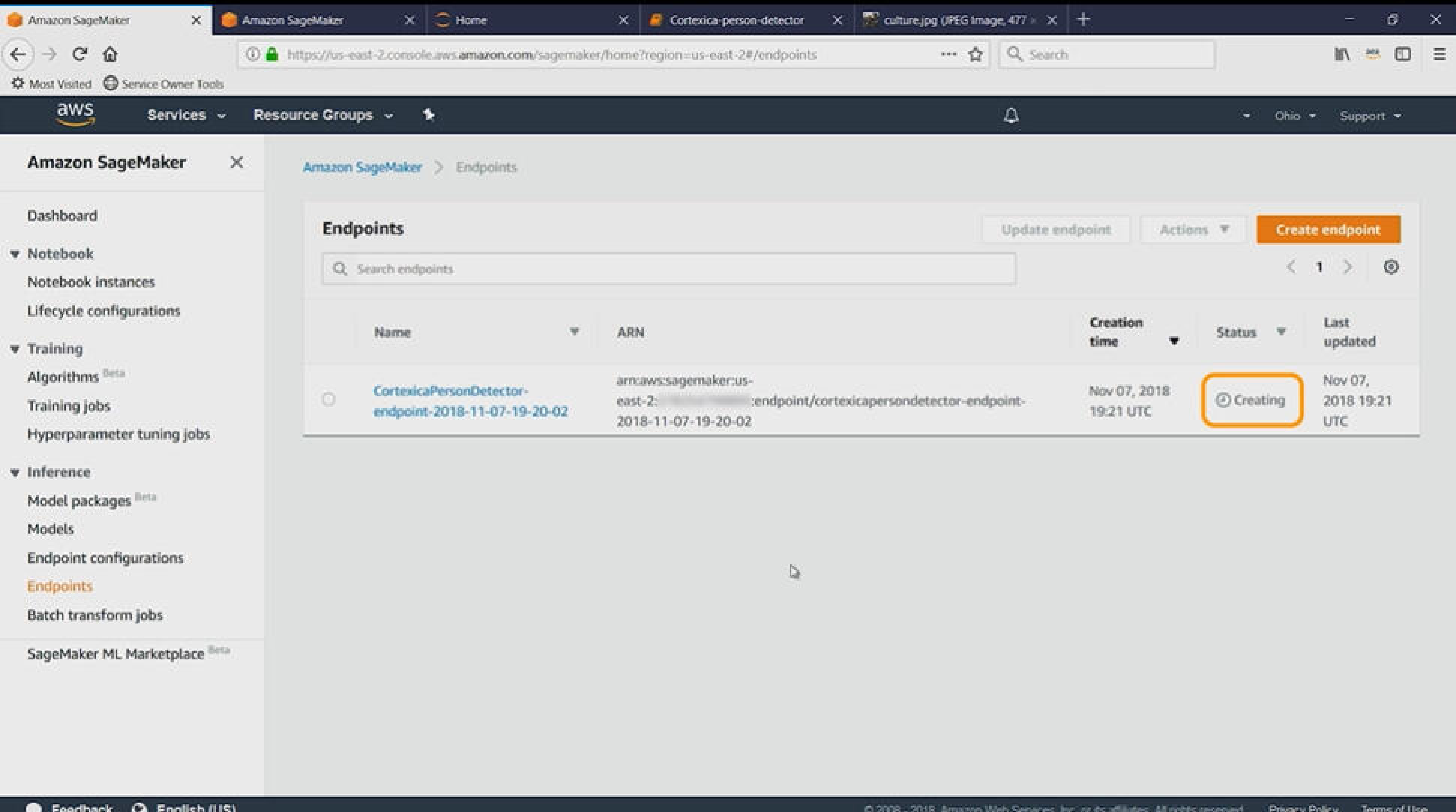
In [ ]:

```
#specify input image
url='https://www.amazondelivers.jobs/media/16938/culture.jpg'

#url='https://d2908q01vomqb2.cloudfront.net/cb4e5208b4cd87268b208e49452ed6e89a68e0b8/2018/02/08/smallpdf-webteam-1024x76
```

In [ ]:

```
#Download the input image
```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https://us-east-2.console.aws.amazon.com/sagemaker/home?region=us-east-2#/endpoints
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ARN
Creation time
Status
Last updated
CortexicaPersonDetector-endpoint-2018-11-07-19-20-02
arn:aws:sagemaker:us-east-2: :endpoint/cortexicapersondetector-endpoint-2018-11-07-19-20-02
Nov 07, 2018 19:21 UTC
Creating
Nov 07, 2018 19:21 UTC
Feedback
English (US)
Privacy Policy
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Run | Code

```
    EndpointName=endPointName,
    EndpointConfigName=endPointConfigName,
    Tags=[{
            'Key': 'test-type',
            'Value': 'cortexica-model-testing'
        }])
create_endpoint_response
```

Out[6]:

```
{'EndpointArn': 'arn:aws:sagemaker:us-east-2:[illegible]:endpoint/cortexicapersondetector-endpoint-2018-11-07-19-20-02',
 'ResponseMetadata': {'RequestId': '39a3ec54-269a-4870-8c32-c0ce90c0bc04',
  'HTTPStatusCode': 200,
  'HTTPHeaders': {'x-amzn-requestid': '39a3ec54-269a-4870-8c32-c0ce90c0bc04',
   'content-type': 'application/x-amz-json-1.1',
   'content-length': '120',
   'date': 'Wed, 07 Nov 2018 19:21:09 GMT'},
  'RetryAttempts': 0}}
```

In [ ]:

```
#specify input image
url='https://www.amazondelivers.jobs/media/16938/culture.jpg'

#url='https://d2908q01vomqb2.cloudfront.net/cb4e5208b4cd87268b208e49452ed6e89a68e0b8/2018/02/08/smallpdf-webteam-1024x76
```

In [ ]:

```
#Download the input image
urllib.request.urlretrieve(url,'input.jpg')
```

In [ ]:

```
#Perform real-time prediction

#endPointName='my-endpoint-2018-11-07-02-10-30'

runtime = boto3.client('sagemaker-runtime')
with open("input.jpg", "rb") as imageFile:
  f = imageFile.read()
  b = bytearray(f)
output=runtime.invoke_endpoint(EndpointName=endPointName,Body=b,Accept="image/jpeg", ContentType='image/jpeg')
print(output)
```

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Run | Code

```
    EndpointName=endPointName,
    EndpointConfigName=endPointConfigName,
    Tags=[{
            'Key': 'test-type',
            'Value': 'cortexica-model-testing'
        }])
create_endpoint_response
```

Out[6]:
```
{'EndpointArn': 'arn:aws:sagemaker:us-east-2:[illegible]:endpoint/cortexicapersondetector-endpoint-2018-11-07-19-20-02',
 'ResponseMetadata': {'RequestId': '39a3ec54-269a-4870-8c32-c0ce90c0bc04',
  'HTTPStatusCode': 200,
  'HTTPHeaders': {'x-amzn-requestid': '39a3ec54-269a-4870-8c32-c0ce90c0bc04',
   'content-type': 'application/x-amz-json-1.1',
   'content-length': '120',
   'date': 'Wed, 07 Nov 2018 19:21:09 GMT'},
  'RetryAttempts': 0}}
```

In [ ]:
```
#specify input image
url='https://www.amazondelivers.jobs/media/16938/culture.jpg'

#url='https://d2908q01vomqb2.cloudfront.net/cb4e5208b4cd87268b208e49452ed6e89a68e0b8/2018/02/08/smallpdf-webteam-1024x76
```

In [ ]:
```
#Download the input image
urllib.request.urlretrieve(url,'input.jpg')
```

In [ ]:
```
#Perform real-time prediction

#endPointName='my-endpoint-2018-11-07-02-10-30'

runtime = boto3.client('sagemaker-runtime')
with open("input.jpg", "rb") as imageFile:
  f = imageFile.read()
  b = bytearray(f)
output=runtime.invoke_endpoint(EndpointName=endPointName,Body=b,Accept="image/jpeg", ContentType='image/jpeg')
print(output)
```

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Run | Code

```
    EndpointName=endPointName,
    EndpointConfigName=endPointConfigName,
    Tags=[{
            'Key': 'test-type',
            'Value': 'cortexica-model-testing'
        }])
create_endpoint_response
```

Out[6]:

```
{'EndpointArn': 'arn:aws:sagemaker:us-east-2:[illegible]:endpoint/cortexicapersondetector-endpoint-2018-11-07-19-20-02',
 'ResponseMetadata': {'RequestId': '39a3ec54-269a-4870-8c32-c0ce90c0bc04',
  'HTTPStatusCode': 200,
  'HTTPHeaders': {'x-amzn-requestid': '39a3ec54-269a-4870-8c32-c0ce90c0bc04',
   'content-type': 'application/x-amz-json-1.1',
   'content-length': '120',
   'date': 'Wed, 07 Nov 2018 19:21:09 GMT'},
  'RetryAttempts': 0}}
```

In [ ]:

```
#specify input image
url='https://www.amazondelivers.jobs/media/16938/culture.jpg'

#url='https://d2908q01vomqb2.cloudfront.net/cb4e5208b4cd87268b208e49452ed6e89a68e0b8/2018/02/08/smallpdf-webteam-1024x76
```

In [ ]:

```
#Download the input image
urllib.request.urlretrieve(url,'input.jpg')
```

In [ ]:

```
#Perform real-time prediction

#endPointName='my-endpoint-2018-11-07-02-10-30'

runtime = boto3.client('sagemaker-runtime')
with open("input.jpg", "rb") as imageFile:
  f = imageFile.read()
  b = bytearray(f)
output=runtime.invoke_endpoint(EndpointName=endPointName,Body=b,Accept="image/jpeg", ContentType='image/jpeg')
print(output)
```

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Run   Code

```
    EndpointName=endPointName,
    EndpointConfigName=endPointConfigName,
    Tags=[{
            'Key': 'test-type',
            'Value': 'cortexica-model-testing'
        }])
create_endpoint_response
```

Out[6]:

```
{'EndpointArn': 'arn:aws:sagemaker:us-east-2:[illegible]:endpoint/cortexicapersondetector-endpoint-2018-11-07-19-20-02',
 'ResponseMetadata': {'RequestId': '39a3ec54-269a-4870-8c32-c0ce90c0bc04',
  'HTTPStatusCode': 200,
  'HTTPHeaders': {'x-amzn-requestid': '39a3ec54-269a-4870-8c32-c0ce90c0bc04',
   'content-type': 'application/x-amz-json-1.1',
   'content-length': '120',
   'date': 'Wed, 07 Nov 2018 19:21:09 GMT'},
  'RetryAttempts': 0}}
```

In [7]:

```
#specify input image
url='https://www.amazondelivers.jobs/media/16938/culture.jpg'

#url='https://d2908q01vomqb2.cloudfront.net/cb4e5208b4cd87268b208e49452ed6e89a68e0b8/2018/02/08/smallpdf-webteam-1024x76
```

In [ ]:

```
#Download the input image
urllib.request.urlretrieve(url,'input.jpg')
```

In [ ]:

```
#Perform real-time prediction

#endPointName='my-endpoint-2018-11-07-02-10-30'

runtime = boto3.client('sagemaker-runtime')
with open("input.jpg", "rb") as imageFile:
  f = imageFile.read()
  b = bytearray(f)
output=runtime.invoke_endpoint(EndpointName=endPointName,Body=b,Accept="image/jpeg", ContentType='image/jpeg')
print(output)
```

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Run | Code

```
  'content-length': '120',
  'date': 'Wed, 07 Nov 2018 19:21:09 GMT'},
 'RetryAttempts': 0}}
```

In [7]:
```
#specify input image
url='https://www.amazondelivers.jobs/media/16938/culture.jpg'

#url='https://d2908q01vomgb2.cloudfront.net/cb4e5208b4cd87268b208e49452ed6e89a68e0b8/2018/02/08/smallpdf-webteam-1024x76
```

In [8]:
```
#Download the input image
urllib.request.urlretrieve(url,'input.jpg')
```

Out[8]: `('input.jpg', <http.client.HTTPMessage at 0x7f2793f8bf98>)`

In [ ]:
```
#Perform real-time prediction

#endPointName='my-endpoint-2018-11-07-02-10-30'

runtime = boto3.client('sagemaker-runtime')
with open("input.jpg", "rb") as imageFile:
  f = imageFile.read()
  b = bytearray(f)
output=runtime.invoke_endpoint(EndpointName=endPointName,Body=b,Accept="image/jpeg", ContentType='image/jpeg')
print(output)
data= output['Body'].read()

fh = open("output" + timestamp + ".jpeg", "wb")
fh.write(data)
fh.close()
```

In [ ]:
```
#Lets upload data to S3

batch_job_name='Cortexica-batchJob-'+timestamp

batch_input = session.upload_data("input.jpg", bucket, "data()/Cortexica-batch_input".format(timestamp))
```

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Run Code

```
  'content-length': '120',
  'date': 'Wed, 07 Nov 2018 19:21:09 GMT'},
 'RetryAttempts': 0}}
```

In [7]:
```
#specify input image
url='https://www.amazondelivers.jobs/media/16938/culture.jpg'

#url='https://d2908q01vomgb2.cloudfront.net/cb4e5208b4cd87268b208e49452ed6e89a68e0b8/2018/02/08/smallpdf-webteam-1024x76
```

In [8]:
```
#Download the input image
urllib.request.urlretrieve(url,'input.jpg')
```

Out[8]: ('input.jpg', <http.client.HTTPMessage at 0x7f2793f8bf98>)

In [ ]:
```
#Perform real-time prediction

#endPointName='my-endpoint-2018-11-07-02-10-30'

runtime = boto3.client('sagemaker-runtime')
with open("input.jpg", "rb") as imageFile:
  f = imageFile.read()
  b = bytearray(f)
output=runtime.invoke_endpoint(EndpointName=endPointName,Body=b,Accept="image/jpeg", ContentType='image/jpeg')
print(output)
data= output['Body'].read()

fh = open("output" + timestamp + ".jpeg", "wb")
fh.write(data)
fh.close()
```

In [ ]:
```
#Lets upload data to S3

batch_job_name='Cortexica-batchJob-'+timestamp

batch_input = session.upload_data("input.jpg", bucket, "data{}/Cortexica-batch_input".format(timestamp))
```

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Run   Code

```
url='https://www.amazondelivers.jobs/media/16938/culture.jpg'

#url='https://d2908q01vomqb2.cloudfront.net/cb4e5208b4cd87268b208e49452ed6e89a68e0b8/2018/02/08/smallpdf-webteam-1024x76
```

In [8]:

```
#Download the input image
urllib.request.urlretrieve(url,'input.jpg')
```

Out[8]:

```
('input.jpg', <http.client.HTTPMessage at 0x7f2793f8bf98>)
```

In [ ]:

```
#Perform real-time prediction

#endPointName='my-endpoint-2018-11-07-02-10-30'

runtime = boto3.client('sagemaker-runtime')
with open("input.jpg", "rb") as imageFile:
  f = imageFile.read()
  b = bytearray(f)
output=runtime.invoke_endpoint(EndpointName=endPointName,Body=b,Accept="image/jpeg", ContentType='image/jpeg')
print(output)
data= output['Body'].read()

fh = open("output" + timestamp + ".jpeg", "wb")
fh.write(data)
fh.close()
```

In [ ]:

```
#Lets upload data to S3

batch_job_name='Cortexica-batchJob-'+timestamp

batch_input = session.upload_data("input.jpg", bucket, "data{}/Cortexica-batch_input".format(timestamp))
"uploaded training data file to {}".format(batch_input)
```

In [ ]:

```
%%time

batch_output = 's3://{}/{}/output'.format(bucket, batch_job_name)
```

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Run | Code

In [7]:

```
#specify input image
url='https://www.amazondelivers.jobs/media/16938/culture.jpg'

#url='https://d2908q01vomqb2.cloudfront.net/cb4e5208b4cd87268b208e49452ed6e89a68e0b8/2018/02/08/smallpdf-webteam-1024x76
```

In [8]:

```
#Download the input image
urllib.request.urlretrieve(url,'input.jpg')
```

Out[8]: ('input.jpg', <http.client.HTTPMessage at 0x7f2793f8bf98>)

In [10]:

```
#Perform real-time prediction

#endPointName='my-endpoint-2018-11-07-02-10-30'

runtime = boto3.client('sagemaker-runtime')
with open("input.jpg", "rb") as imageFile:
  f = imageFile.read()
  b = bytearray(f)
output=runtime.invoke_endpoint(EndpointName=endPointName,Body=b,Accept="image/jpeg", ContentType='image/jpeg')
print(output)
data= output['Body'].read()

fh = open("output" + timestamp + ".jpeg", "wb")
fh.write(data)
fh.close()
```

{'ResponseMetadata': {'RequestId': 'cc368f31-e61f-4dac-a25f-9529cb7b941a', 'HTTPStatusCode': 200, 'HTTPHeaders': {'x-amzn-requestid': 'cc368f31-e61f-4dac-a25f-9529cb7b941a', 'x-amzn-invoked-production-variant': 'default-variant-name', 'date': 'Wed, 7 Nov 2018 19:28:05 GMT', 'content-type': 'image/jpeg', 'content-length': '78369'}, 'RetryAttempts': 0}, 'ContentType': 'image/jpeg', 'InvokedProductionVariant': 'default-variant-name', 'Body': <botocore.response.StreamingBody object at 0x7f2793fee240>}

In [ ]:

```
#Lets upload data to S3

batch_job_name='Cortexica-batchJob-'+timestamp
```

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sdk		11 days ago	
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train_data		11 days ago	
Untitled Folder		8 days ago	
Cortexica-person-detector-Copy1.ipynb	Running	16 hours ago	23.4 kB
Cortexica-person-detector.ipynb	Running	5 minutes ago	16.1 kB
Free-Model-testing-Wipro-EKYC-financials.ipynb	Running	7 days ago	21.3 kB
H20 - sample notebook.ipynb	Running	a day ago	17.9 kB
Perform-prediction-on-a-model.ipynb	Running	7 days ago	143 kB
sagemaker_marketplace_deployment.ipynb	Running	5 days ago	24.9 kB
spotlight_implicit_factorization-my-notebook.ipynb	Running	2 days ago	49.8 kB
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input.png		15 hours ago	1.15 MB
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output-2018-11-07-01-56-00.jpeg		17 hours ago	46 kB
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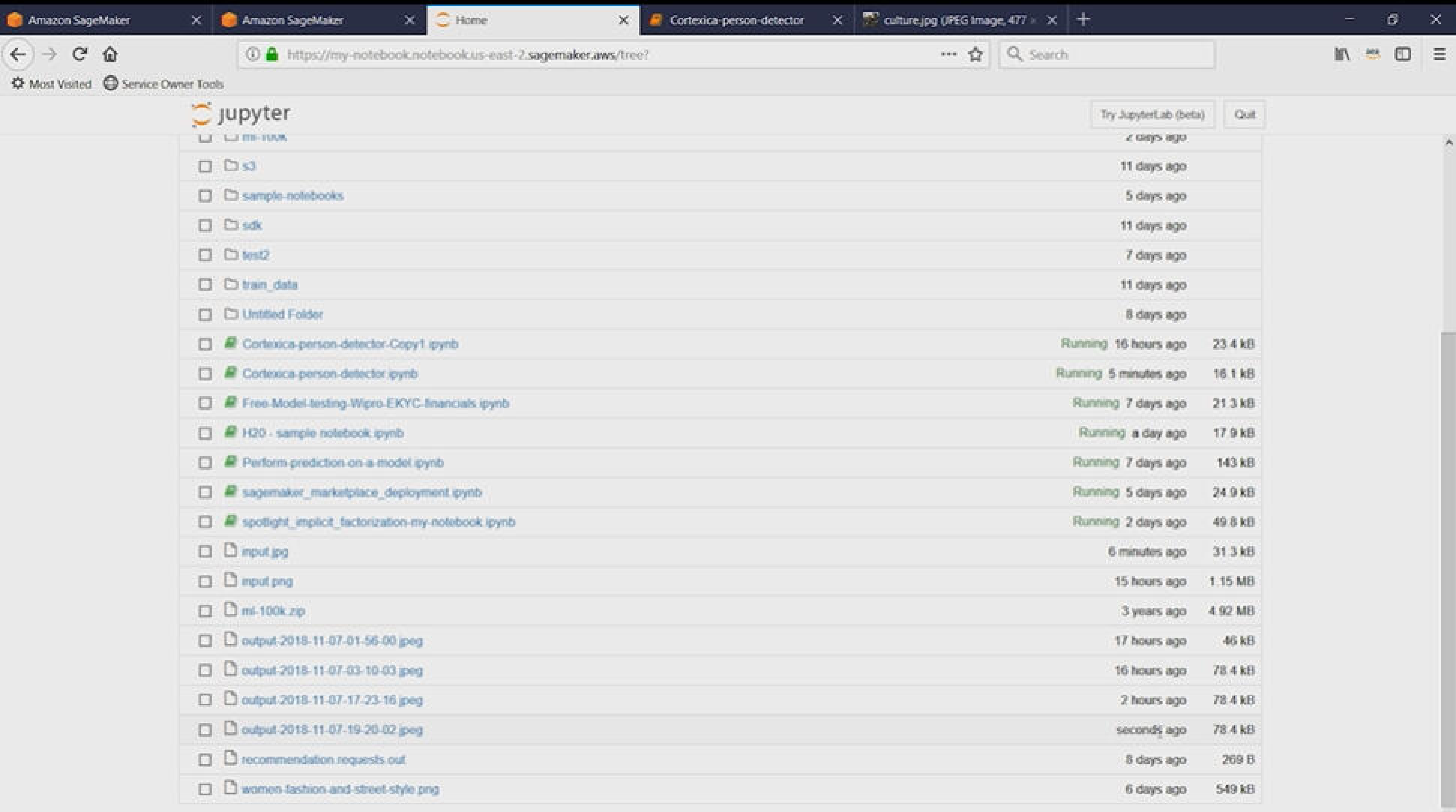
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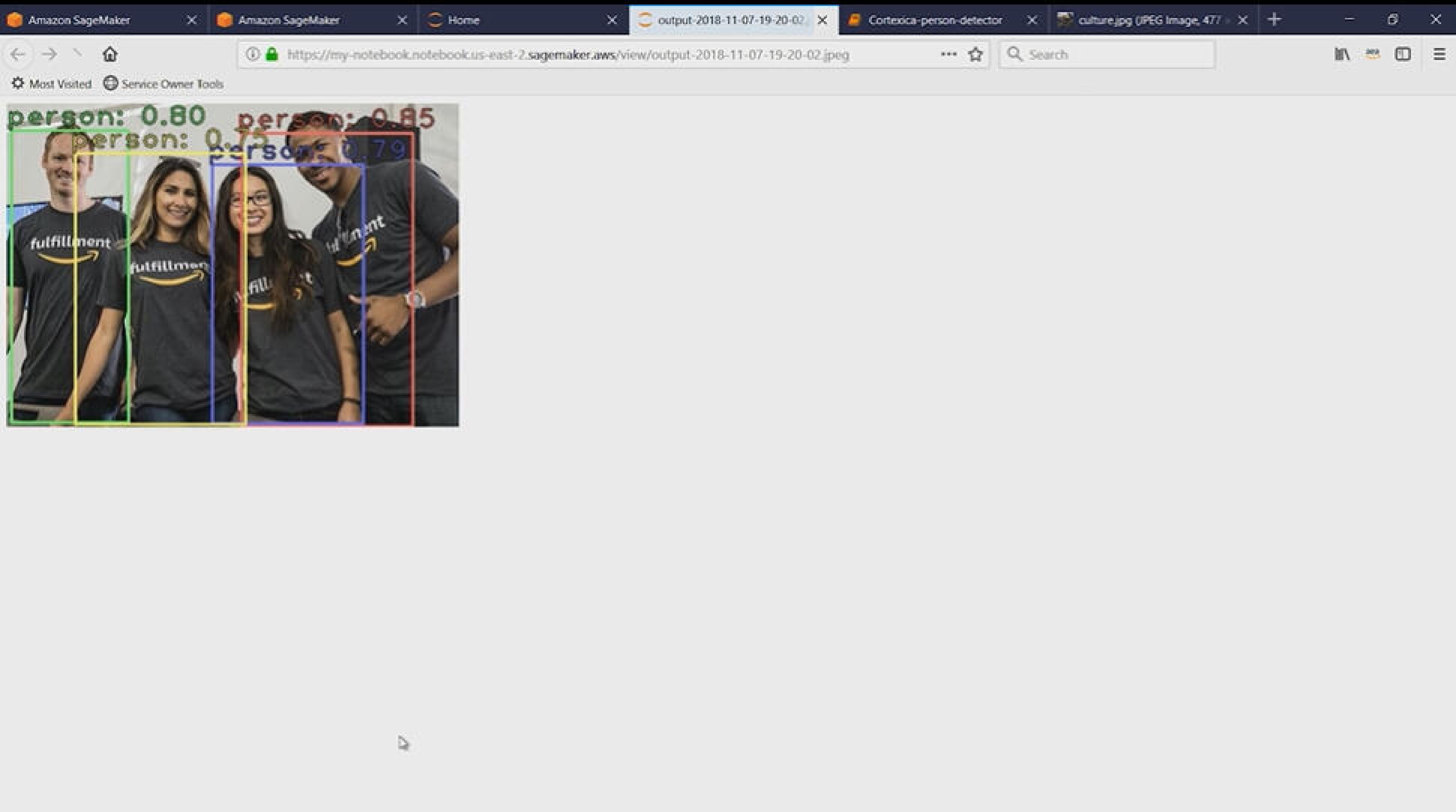
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