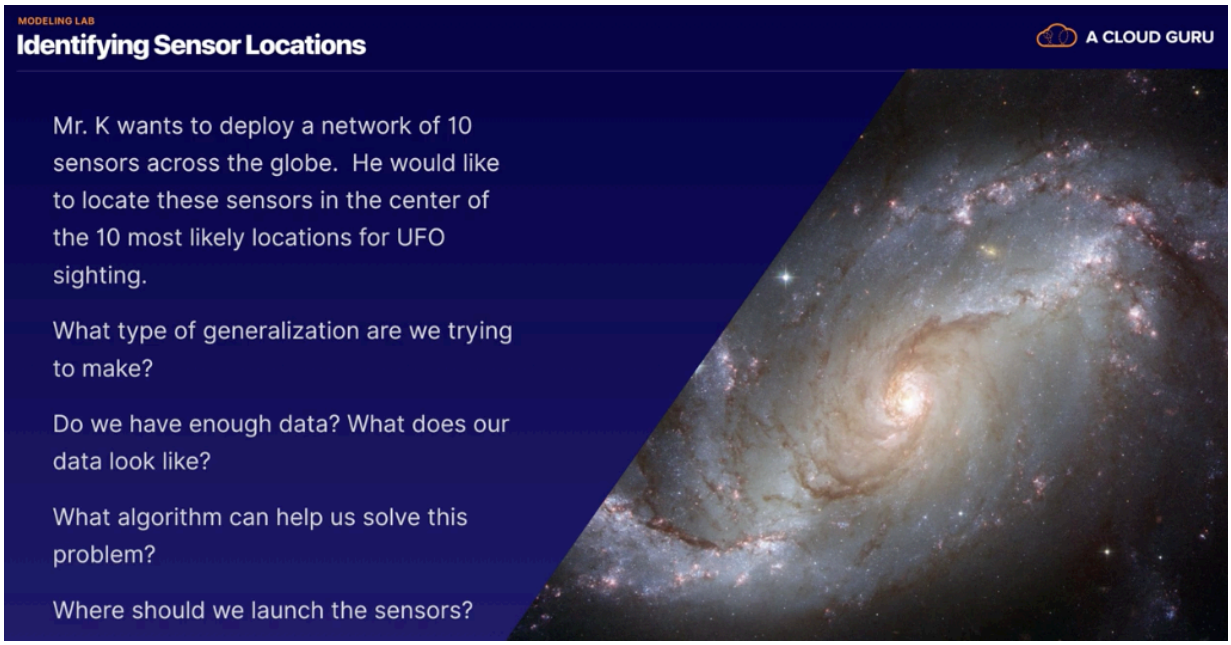
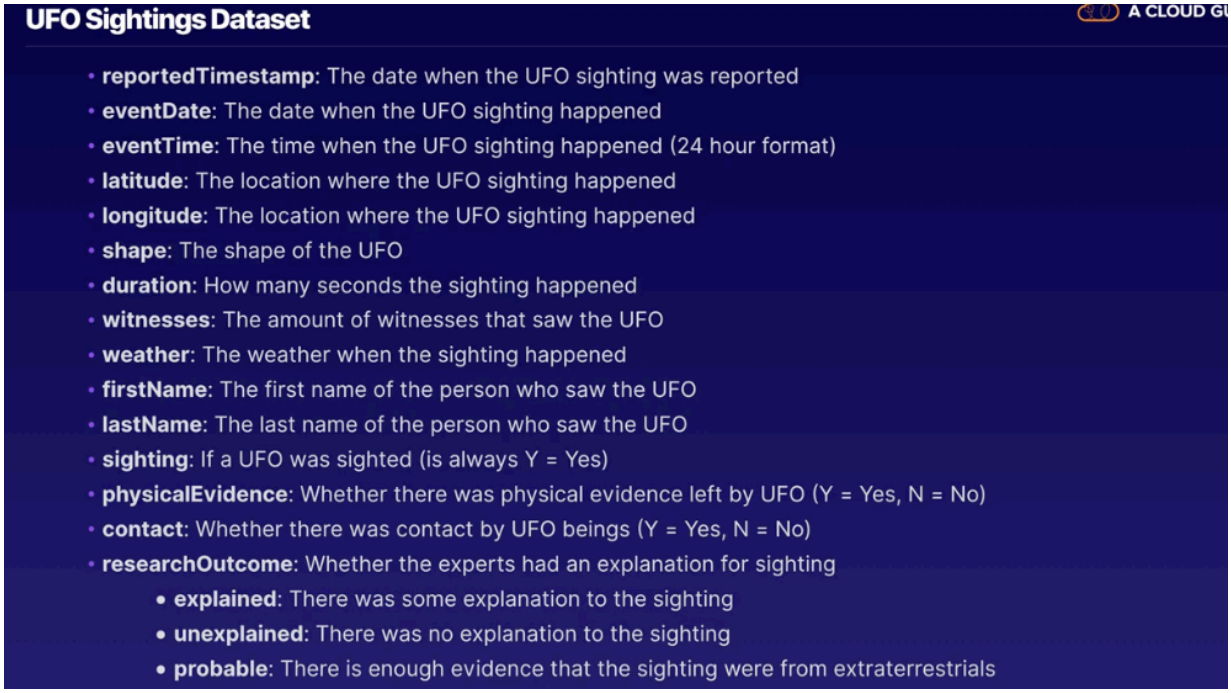
Cloud Guru - 5 - Modeling Lab

https://acloud.guru/course/aws-certified-machine-learning-specialty/learn/87700af1-74be-5d7b-2143-9e031dd0fb1d/21ddf3e2-05df-c4db-a8df-877d8c5d52e3/watch?backUrl=~2Fcourses&backUrl=~2Fcourses&backUrl=~2Fcourses,~2Fcourses

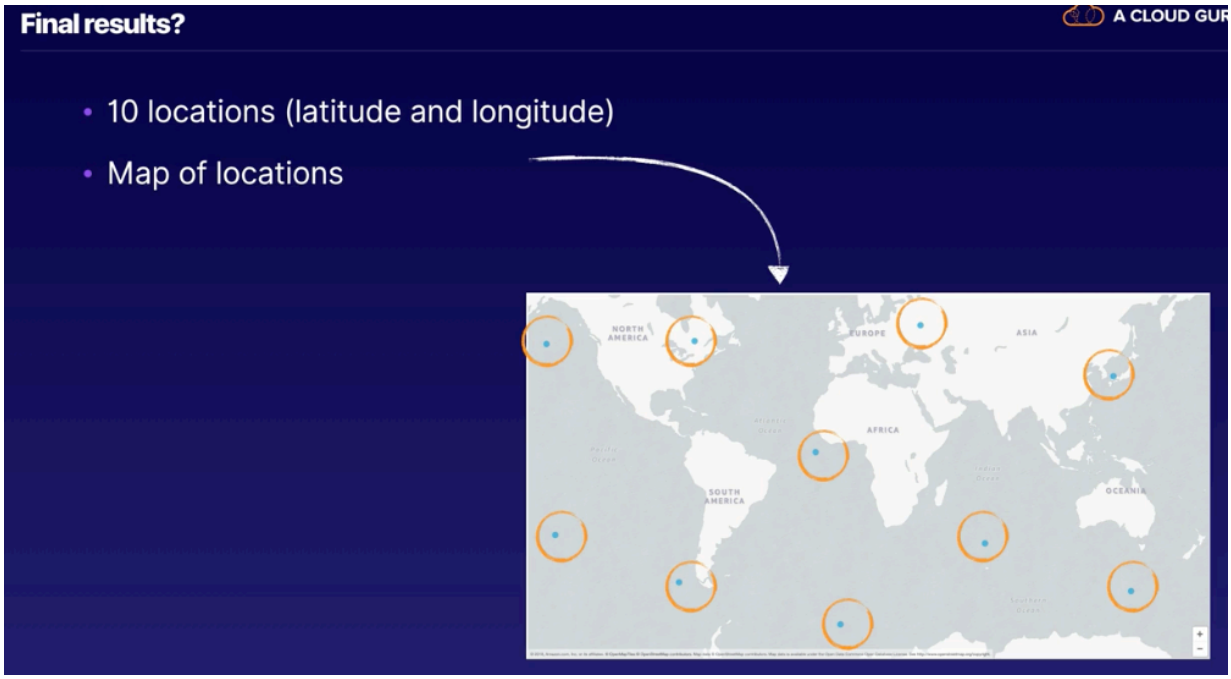


A sensor would look like something like this:

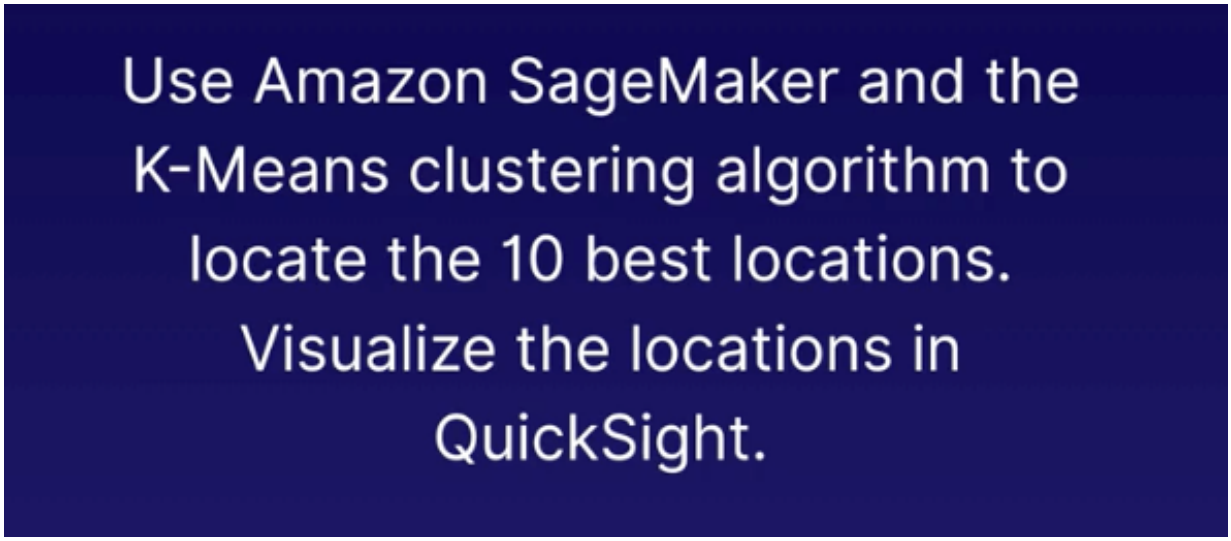
Data set (synthetic):

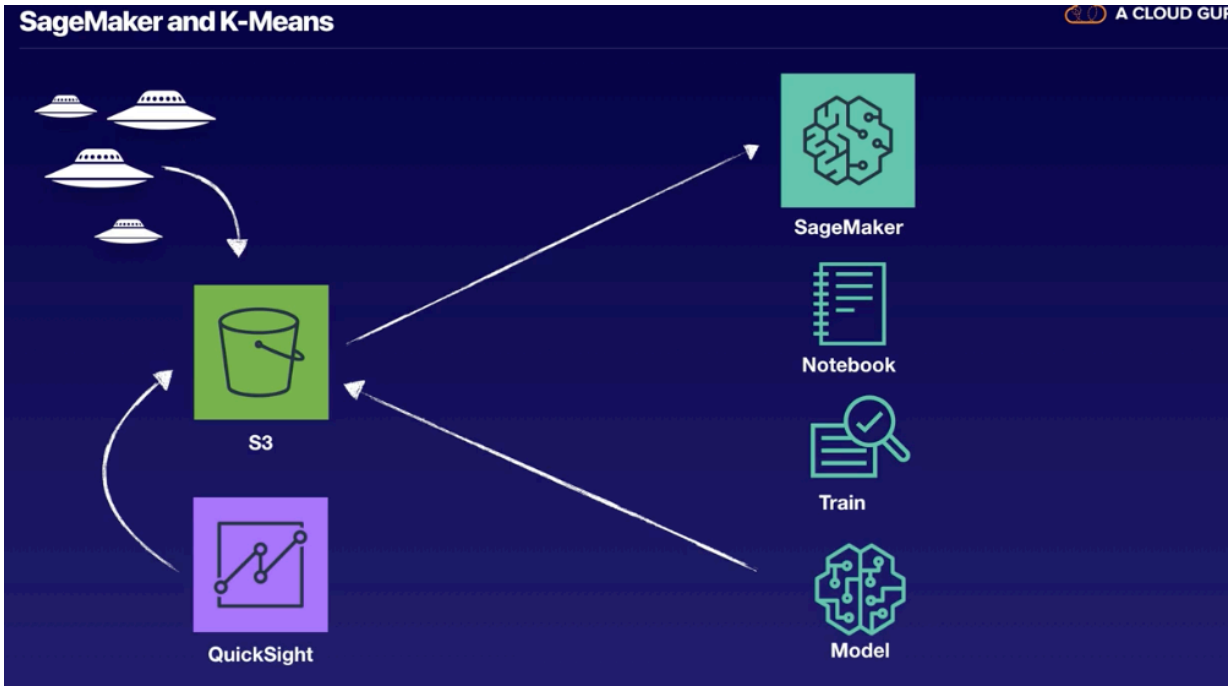


Find 10 locations and map them

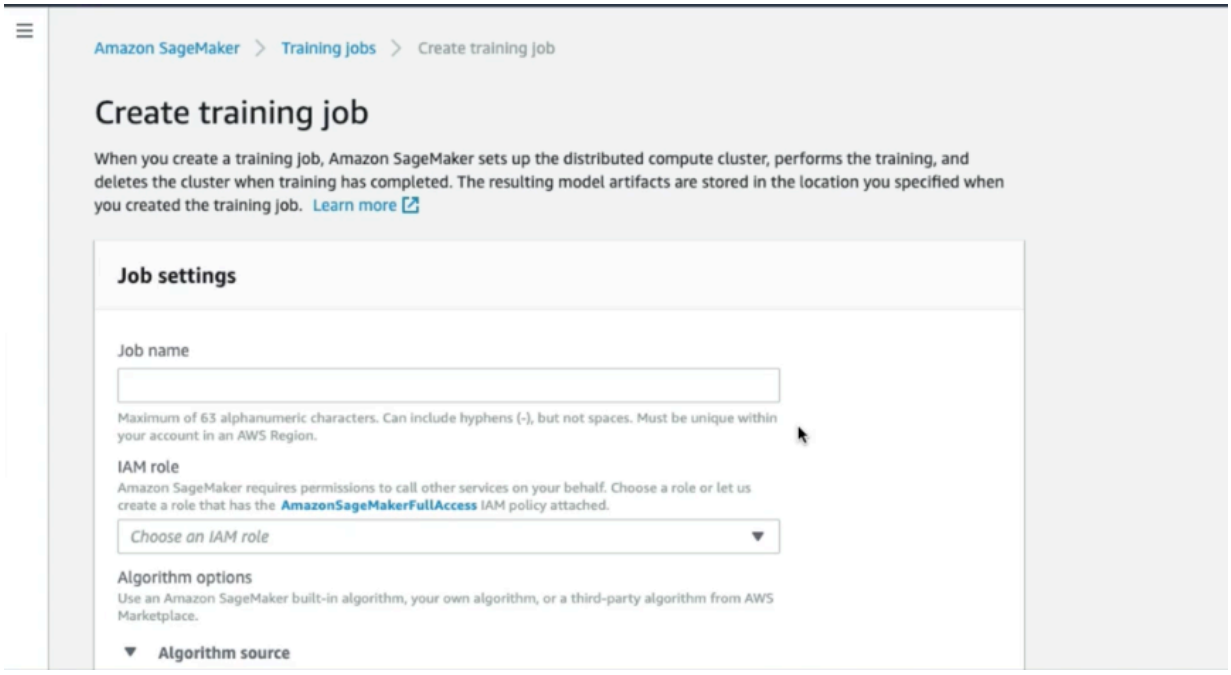

Final results?
A CLOUD GUR
• 10 locations (latitude and longitude)
• Map of locations
NORTH AMERICA
EUROPE
ASIA
AFRICA
SOUTH AMERICA
OCEANIA

Approach:

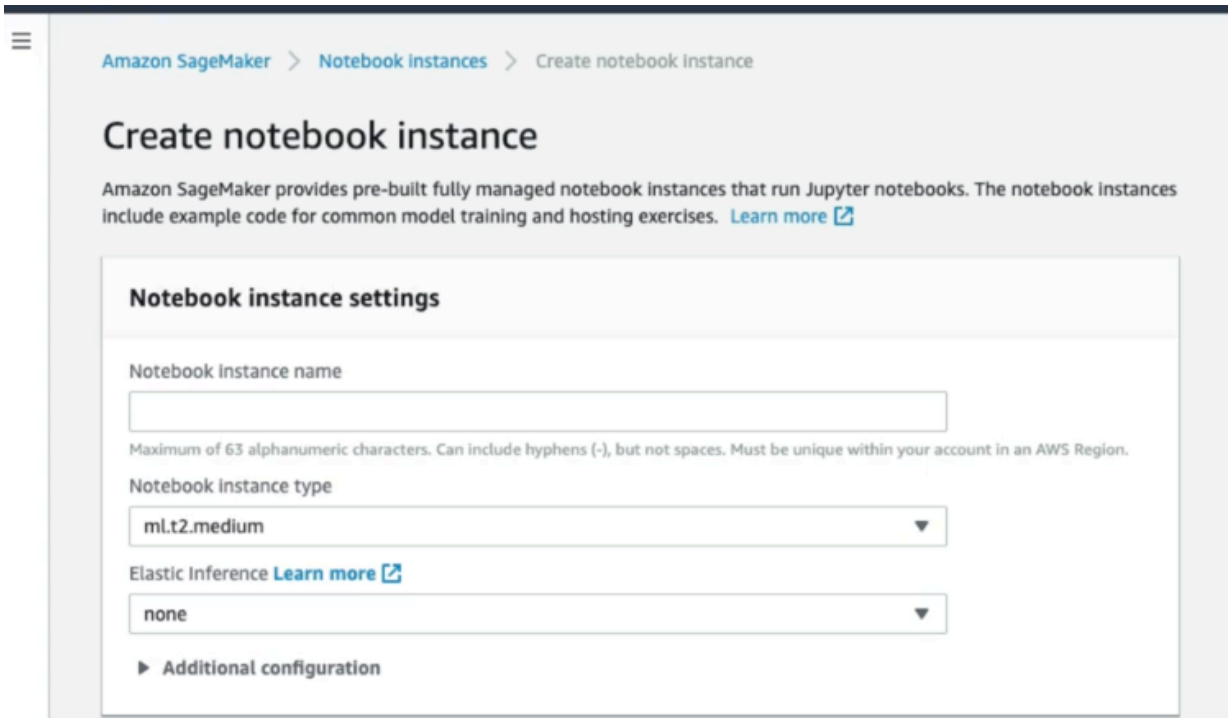

Use Amazon SageMaker and the K-Means clustering algorithm to locate the 10 best locations. Visualize the locations in QuickSight.



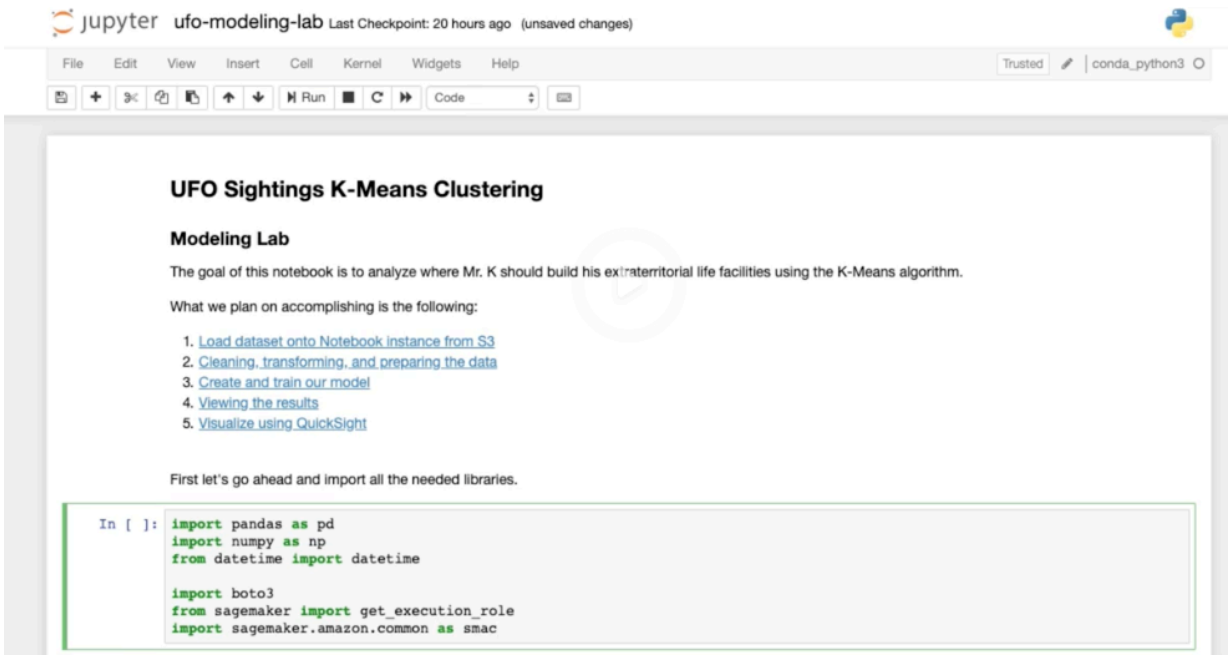
To note we could create a Training job with SageMaker IDE



But we are going to use a notebook instead.



Then we can upload the notebook, or Crete a new one from scratch.
Conda-python3 env



Create Data Frame with UFO data set

Step 1: Loading the data from Amazon S3

Next, lets get the UFO sightings data that is stored in S3.

```
In [2]: role = get_execution_role()
        bucket = 'ml-labs-acg'
        prefix = 'ufo_dataset'
        data_key = 'ufo_fullset.csv'
        data_location = 's3://{}/{}/{}'.format(bucket, prefix, data_key)

        df = pd.read_csv(data_location, low_memory=False)
```

```
In [3]: df.head()
```

Out[3]:

	reportedTimestamp	eventDate	eventTime	shape	duration	witnesses	weather	firstName	lastName	latitude	longitude	sighting	physicalEvidence
0	1982-11-29T10:01:48.297Z	1982-11-28	03:17	oval	71	1	snow	Muriel	Bartell	28.039167	-81.950000	Y	N
1	2006-03-05T18:36:08.186Z	2006-03-05	04:56	light	75	1	partly cloudy	Floy	Heaney	33.660278	-117.998333	Y	Y
2	2002-07-31T23:33:55.223Z	2002-07-26	13:43	oval	25	1	rain	Evelyn	Champlin	41.325278	-72.193611	Y	Y
3	1986-08-31T00:50:08.017Z	1986-08-27	16:12	sphere	47	1	mostly cloudy	Holden	Ward	38.254167	-85.759444	Y	N
4	2004-09-26T08:47:39.860Z	2004-09-25	17:21	disk	59	1	rain	Abigayle	Grady	22.308085	69.600603	Y	N

Rows and attributes: 18k rows and 15 columns (attributes)

```
In [4]: df.shape
Out[4]: (18000, 15)
```

Step 2: Cleaning, transforming, and preparing the data

Create another DataFrame with just the latitude and longitude attributes

```
In [5]: df_geo = df[['latitude', 'longitude']]
```

```
In [6]: df_geo.head()
```

Out[6]:

	latitude	longitude
0	28.039167	-81.950000
1	33.660278	-117.998333
2	41.325278	-72.193611
3	38.254167	-85.759444
4	22.308085	69.600603

```
In [7]: df_geo.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 18000 entries, 0 to 17999
Data columns (total 2 columns):
latitude     18000 non-null float64
longitude    18000 non-null float64
dtypes: float64(2)
memory usage: 281.3 KB
```

```
In [8]: missing_values = df_geo.isnull().values.any()
        print('Are there any missing values? {}'.format(missing_values))
        if(missing_values):
            df_geo[df_geo.isnull().any(axis=1)]

        Are there any missing values? False
```

Next, let's go ahead and transform the pandas DataFrame (our dataset) into a numpy.ndarray. When we do this each row is converted to a Record object. According to the documentation, this is what the K-Means algorithm expects as training data. This is what we will use as training data for our model.

See the documentation for input training

K-means reference:
https://sagemaker.readthedocs.io/en/stable/algorithms/kmeans.html
K-means algorithm is expecting float 32 (not 64)

```
In [9]: data_train = df_geo.values.astype('float32')
        data_train

Out[9]: array([[  28.039167,  -81.95    ],
               [  33.66028 , -117.99834 ],
               [  41.32528 ,  -72.19361 ],
               ...,
               [  37.49472 , -120.84556 ],
               [  40.771946,  -73.93056 ],
               [  64.837776, -147.71638 ]], dtype=float32)
```

K-means hyper parameters:
https://docs.aws.amazon.com/sagemaker/latest/dg/k-means-api-config.html

Now build our model

Step 3: Create and train our model

In this step we will import and use the built-in SageMaker K-Means algorithm. We will set the number of cluster to 10 (for our 10 sensors), specify the instance type we want to train on, and the location of where we want our model artifact to live.

See the documentation of hyperparameters here

```
In [ ]: from sagemaker import KMeans

        num_clusters = 10
        output_location = 's3://' + bucket + '/model-artifacts'

        kmeans = KMeans(role=role,
                        train_instance_count=1,
                        train_instance_type='ml.c4.xlarge',
                        output_path=output_location,
                        k=num_clusters)
```

And train our model

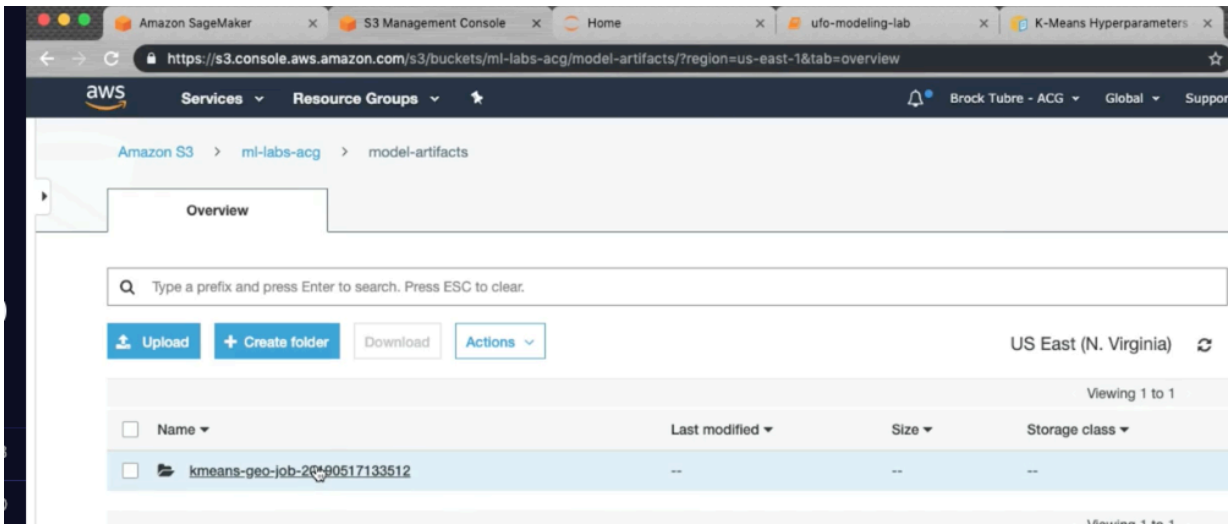
```
In [11]: job_name = 'kmeans-geo-job-{}'.format(datetime.now().strftime("%Y%m%d%H%M%S"))
         print('Here is the job name {}'.format(job_name))

         Here is the job name kmeans-geo-job-20190517133512

In [14]: %%time
         kmeans.fit(kmeans.record_set(data_train), job_name=job_name)

         2019-05-17 13:37:19 Starting - Starting the training job...
         2019-05-17 13:37:21 Starting - Launching requested ML instances......
         2019-05-17 13:38:26 Starting - Preparing the instances for training......
         2019-05-17 13:39:44 Downloading - Downloading input data..

         2019-05-17 13:40:12 Training - Training image download completed. Training in progress.
         2019-05-17 13:40:12 Uploading - Uploading generated training model
         2019-05-17 13:40:12 Completed - Training job completed
         Docker entrypoint called with argument(s): train
         [05/17/2019 13:40:02 INFO 140619722299200] Reading default configuration from /opt/amazon/lib/python2.7/site-package
         s/algorithm/resources/default-input.json: {u'_enable_profiler': u'false', u'_tuning_objective_metric': u'', u'_num_gp
         us': u'auto', u'local_lloyd_num_trials': u'auto', u'_log_level': u'info', u'_kvstore': u'auto', u'local_lloyd_init_me
         thod': u'kmeans++', u'force_dense': u'true', u'epochs': u'1', u'init_method': u'random', u'local_lloyd_tol': u'0.000
         1', u'local_lloyd_max_iter': u'300', u'_disable_wait_to_read': u'false', u'extra_center_factor': u'auto', u'eval_metr
         ics': u'["msd"]', u'_num_kv_servers': u'1', u'mini_batch_size': u'5000', u'half_life_time_size': u'0', u'_num_slice
```

This cell will use our 18000 latitudes and longitudes and create 10 clusters and store that data in S3 in a sub-folder called “model-artifacts”

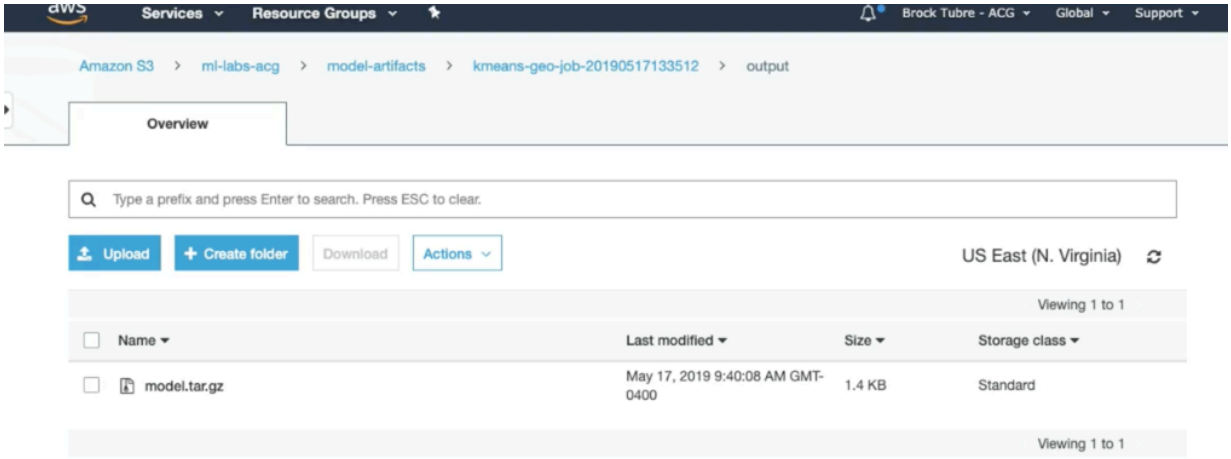
The red is the output of log files from docker image

```
[05/17/2019 13:40:02 INFO 140619722299200] Reading provided configuration from /opt/ml/input/config/hyperparameters.j
son: {u'feature_dim': u'2', u'k': u'10', u'force_dense': u'True'}
[05/17/2019 13:40:02 INFO 140619722299200] Final configuration: {u'_tuning_objective_metric': u'', u'extra_center_fac
tor': u'auto', u'local_lloyd_init_method': u'kmeans++', u'force_dense': u'True', u'epochs': u'1', u'feature_dim':
 u'2', u'local_lloyd_tol': u'0.0001', u'_disable_wait_to_read': u'false', u'eval_metrics': u'["msd"]', u'_num_kv_serv
ers': u'1', u'mini_batch_size': u'5000', u'_enable_profiler': u'false', u'_num_gpus': u'auto', u'local_lloyd_num_tria
ls': u'auto', u'_log_level': u'info', u'init_method': u'random', u'half_life_time_size': u'0', u'local_lloyd_max_ite
r': u'300', u'_kvstore': u'auto', u'k': u'10', u'_num_slices': u'1'}
```

We can now retrieve the results in S3



The mode is located in S3:



We can now deploy it and let people make inferences on it.
We could also deserialize it and see it

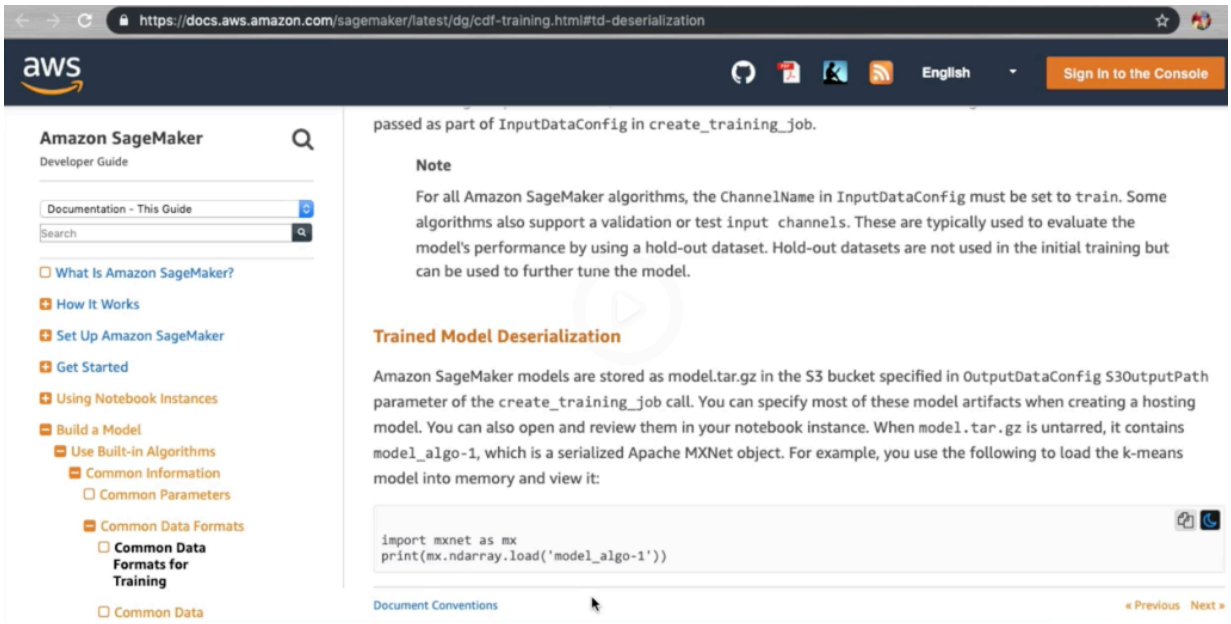
Step 4: Viewing the results

In this step we will take a look at the model artifact SageMaker created for us and stored onto S3. We have to do a few special things to see the latitude and longitude for our 10 clusters (and the center points of those clusters)

See the documentation of deserilization here

At this point we need to "deserilize" the model artifact. Here we are going to open and review them in our notebook instance. We can unzip the model artifact which will contain model_algo-1. This is just a serialized Apache MXNet object. From here we can load that serialized object into a numpy.ndarray and then extract the clustered centroids from the numpy.ndarray.

After we extract the results into a DataFrame of latitudes and longitudes, we can create a CSV with that data, load it onto S3 and then visualize it with QuickSight.



Download model from S3 onto notebook, unzip it

```
In [17]: import os
         model_key = 'model-artifacts/' + job_name + '/output/model.tar.gz'

         boto3.resource('s3').Bucket(bucket).download_file(model_key, 'model.tar.gz')
         os.system('tar -zxvf model.tar.gz')
         os.system('unzip model_algo-1')

Out[17]: 2304
```

Now use MXnet library to deserialize it.
Since it's note installed on the notebook, install it fist

```
In [18]: !pip install mxnet
          (from mxnet) (2.20.1)
         Collecting graphviz<0.9.0,>=0.8.1 (from mxnet)
           Downloading https://files.pythonhosted.org/packages/53/39/4ab213673844e0c004bed8a0781a0721a3f6bb23eb8854ee75c236428
         892/graphviz-0.8.4-py2.py3-none-any.whl
         Requirement already satisfied: urllib3<1.25,>=1.21.1 in /home/ec2-user/anaconda3/envs/python3/lib/python3.6/site-pack
         ages (from requests>=2.20.0->mxnet) (1.23)
         Requirement already satisfied: idna<2.8,>=2.5 in /home/ec2-user/anaconda3/envs/python3/lib/python3.6/site-packages (f
         rom requests>=2.20.0->mxnet) (2.6)
         Requirement already satisfied: certifi>=2017.4.17 in /home/ec2-user/anaconda3/envs/python3/lib/python3.6/site-package
         s (from requests>=2.20.0->mxnet) (2019.3.9)
         Requirement already satisfied: chardet<3.1.0,>=3.0.2 in /home/ec2-user/anaconda3/envs/python3/lib/python3.6/site-pack
         ages (from requests>=2.20.0->mxnet) (3.0.4)
         Installing collected packages: numpy, graphviz, mxnet
           Found existing installation: numpy 1.15.4
             Uninstalling numpy-1.15.4:
               Successfully uninstalled numpy-1.15.4
         Successfully installed graphviz-0.8.4 mxnet-1.4.1 numpy-1.14.6
         You are using pip version 10.0.1, however version 19.1.1 is available.
         You should consider upgrading via the 'pip install --upgrade pip' command.
```

```
In [19]: import mxnet as mx
         Kmeans_model_params = mx.ndarray.load('model_algo-1')
```

Now create a data frame that has the centroid of the clusters

```
In [20]: cluster_centroids_kmeans = pd.DataFrame(Kmeans_model_params[0].asnumpy())
         cluster_centroids_kmeans.columns=df_geo.columns
         cluster_centroids_kmeans
```

Out[20]:

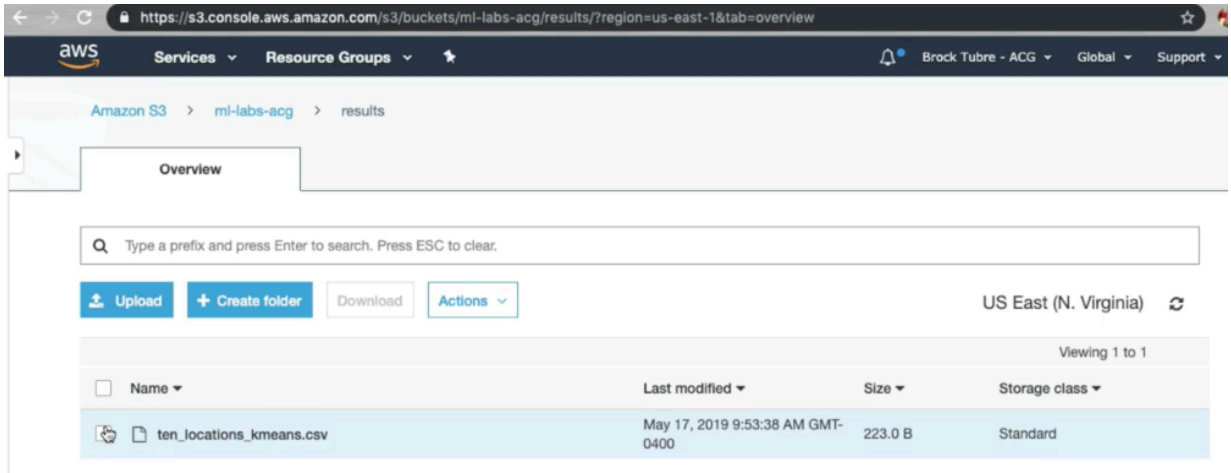
	latitude	longitude
0	41.286369	-74.856453
1	-3.558636	115.825752
2	35.375927	-117.235794
3	48.477852	3.664200
4	36.134438	-97.897385
5	26.707329	-81.378113
6	46.405426	-120.561981
7	25.992533	-146.748108
8	38.832069	-85.299072
9	61.760826	-148.924332

Now convert to CSV and upload to S3

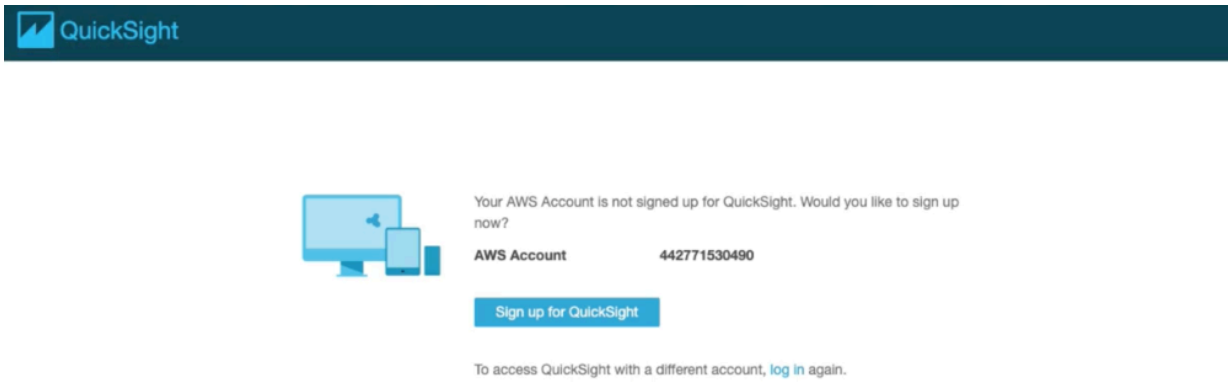
```
In [23]: from io import StringIO

         csv_buffer = StringIO()
         cluster_centroids_kmeans.to_csv(csv_buffer, index=False)
         s3_resource = boto3.resource('s3')
         s3_resource.Object(bucket, 'results/ten_locations_kmeans.csv').put(Body=csv_buffer.getvalue())
```

```
Out[23]: {'ResponseMetadata': {'RequestId': '5B2C5F338C4D94A2',
           'HostId': 'EBaTdqW46uapRaIWfzr0UMENSLV4vuhXsUML53S9b4QC4MP0heG2FEcRYKJqYeSum2J8ikhHdrY=',
           'HTTPStatusCode': 200,
           'HTTPHeaders': {'x-amz-id-2': 'EBaTdqW46uapRaIWfzr0UMENSLV4vuhXsUML53S9b4QC4MP0heG2FEcRYKJqYeSum2J8ikhHdrY=',
            'x-amz-request-id': '5B2C5F338C4D94A2',
            'date': 'Fri, 17 May 2019 13:53:38 GMT',
            'etag': '"51e129efa7a05a163e90bd3fd0433c70"',
            'content-length': '0',
            'server': 'AmazonS3'},
           'RetryAttempts': 0},
          'ETag': '"51e129efa7a05a163e90bd3fd0433c70"'}
```

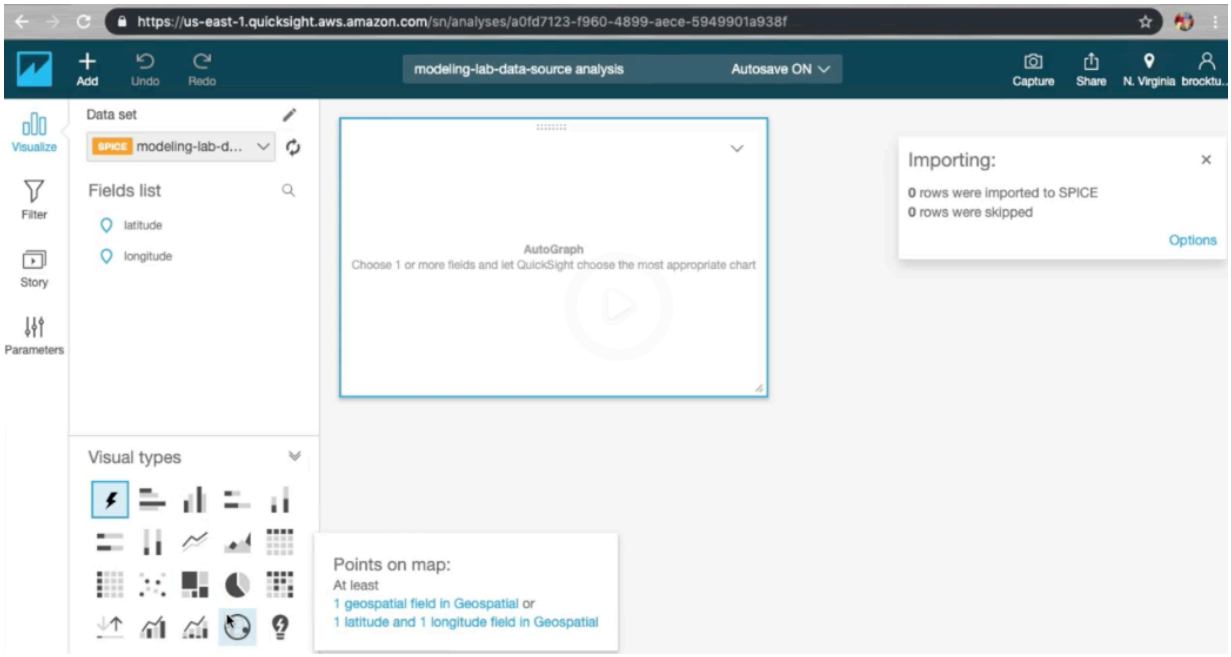
We now have a CSV file with 10 latitudes and longitudes



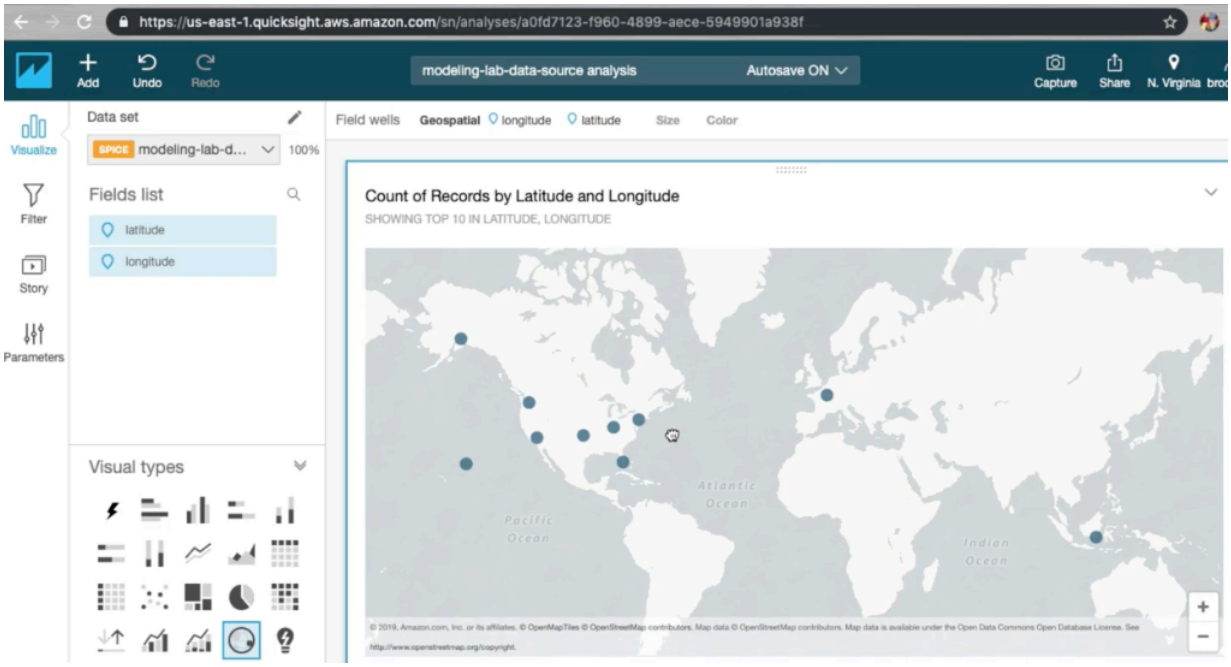
Now we can use it with Quicksight



We select “points on map”



And we can see the map where to launch the sensors


https://us-east-1.quicksight.aws.amazon.com/sn/analyses/a0fd7123-f960-4899-aece-5949901a938f
Add
Undo
Redo
modeling-lab-data-source analysis
Autosave ON
Capture
Share
N. Virginia
Visualize
Filter
Story
Parameters
Data set
SPICE modeling-lab-d...
100%
Fields list
latitude
longitude
Visual types
Field wells
Geospatial
longitude
latitude
Size
Color
Count of Records by Latitude and Longitude
SHOWING TOP 10 IN LATITUDE, LONGITUDE
Pacific Ocean
Atlantic Ocean
Indian Ocean