# Task 3: Advanced (Peter). Machine Learning

#### Looking at a use case

To illustrate this article, let's take one of the most common use cases of Machine Learning: estimating prices of real estate. You have a dataset of past observations, with the characteristics and the selling price of some houses:

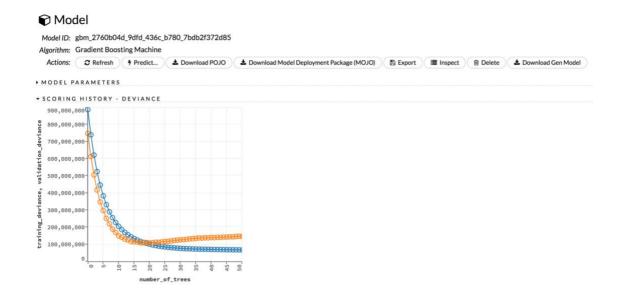
Row	sqft	lot_size_acres		sale_price
1	2231.0	0.3900		251000.0
2	3112.0	0.4400		321000.0
3	2121.0	0.4000	^ ^ /	245000.0
4	2532.0	0.5000		294000.0
5	2632.0	0.4500		285400.0
6	2743.0	0.3700		299000.0
7	2823.0	0.3900		308000.0
8	2918.0	0.4900		321000.0
9	2021.0	0.3700		232000.0

You can build a regression model so that, when there is a new house to sell, you can estimate what the selling price will be.

The training process should be done in batch, from time to time, with a fixed dataset, and will produce a model.

A streaming application can use the model (without updating it), and we may need to update the application when a new model is produced.

### **Creating a ML model with H20**



Go ahead and click on "Download POJO" to get a Java file that looks like this:

## Using the model in a Java application

We are going to use H2O's Gen Model library to interact with the model, so let's add a dependency in our Gradle build:

```
dependencies {
  compile 'ai.h2o:h2o-genmodel:3.20.0.6'
```

```
// other dependencies...
}
```

You must now load the model, prepare a record, then make a prediction:

```
fun main(args: Array<String>) {
    val rawModel = gbm_2760b04d_9dfd_436c_b780_7bdb2f372d85()
    /** TO DO Model **/
    val row = RowData().apply {
        put("sqft", 2342.0)
        put("lot_size_acres", 0.4)
        put("stories", 1.0)
        put("number_bedrooms", 3.0)
        put("number_bathrooms", 3.0)
        put("attached_garage", "yes")
        put("has_pool", "no")
        put("has_kitchen_island", "yes")
        put("main_flooring_type", "hardwood")
        put("has_granite_counters", "yes")
        put("house_age_years", 4.0)
    /** TO DO prediction **/
    println("Prediction: \$${prediction.value}")
```

If we run this code, we get something like:

```
Prediction: $290591.70578645257
```

Great, we just used our Machine Learning model in a standalone application!

# Using the model in a Kafka Streams application

I put together a basic producer that pushes *unlabeled records* to a Kafka topic called housing. The data is in JSON:

```
$ kafka-console-consumer --bootstrap-server localhost:9092 --topic housing

{"sqft":2572,"lot_size_acres":0.2318716,"stories":2,"number_bedrooms":1,"numb
er_bathrooms":0,"attached_garage":false,"has_pool":true,"has_kitchen_island":
true,"main_flooring_type":"hardwood","has_granite_counters":false,"house_age_
years":18}

{"sqft":1256,"lot_size_acres":0.774486,"stories":2,"number_bedrooms":1,"numbe
r_bathrooms":2,"attached_garage":false,"has_pool":false,"has_kitchen_island":
true,"main_flooring_type":"hardwood","has_granite_counters":false,"house_age_
years":3}

{"sqft":2375,"lot_size_acres":0.7467226,"stories":2,"number_bedrooms":4,"numb
er_bathrooms":0,"attached_garage":false,"has_pool":true,"has_kitchen_island":
false,"main_flooring_type":"hardwood","has_granite_counters":true,"house_age_
years":3}
...
```

You must build a <u>Kafka Streams</u> application to process this stream and make predictions as new records arrive.

Now, if we look at the output topic, we can see the input data enhanced with predicted selling prices:

```
$ kafka-console-consumer --bootstrap-server localhost:9092 --topic
predictions

{"sqft":2572,"lot_size_acres":0.2318716,...,"selling_price":297625}

{"sqft":1256,"lot_size_acres":0.774486,...,"selling_price":254118}
```

```
{"sqft":2375,"lot_size_acres":0.7467226,...,"selling_price":303408}
...
```

#### **Conclusion**

You must embed a Machine Learning model in a Kafka Streams application. The model was built outside of the streaming pipeline, and the generated POJO was completely independent from the platform where the model was trained.

Let us know if it helped!