# prescriptive analytics for equity derivative

#python #FinancialDerivatives #pricing #simulation #gbm #prescriptiveanalytics

## The case

Pricing. We want to support the design of a financial contract with algorithmic trading rules: every day, a buy or a sell order for a certain instrument are issued to the market whenever certain conditions are met. The name of such type of contract, in our case, is 'knock-in knock-out equity accumulator'.

Calculating the probability distribution of the NPV of such instrument usually require a couple of minutes on a common desktop machine with fixed, predefined algo-trading rules. Giving a try to multiple combinations of rules may require a full day.

Goal-seeking. We can transform the algo trading rules in parameters that are modified within an iterative test, and we keep track of the parameter's values that resulted in a probability distribution of NPV that meets our requirements (for example: Roy's SFRatio - we choose the scenario with the lowest downside risk).

Parallel work. We take the algorithm and we choose the parallel framework that requires the minimum of code modification, and we deploy and run on the cloud, on a scalable architecture.

We present the project in accordance with the CRISP-DM framework.

## The business issue

### Background

We want to setup an environment for the definition of an equity derivative financial contract based on user-defined 'draft' rules and we want to finalize those rules through a simulation model.

### Objectives and success criteria

We want our simulations to identify the set of hardcoded algorithmic trading rules that minimize the shortfall risk.

# Requirements, Assumptions, and Constraints

## Key financial assumptions and limits of the pricing function

The "profit" calculation implemented in our program is not going to be a valid financial calculation. The main limitations and assumptions are:

- fixed drift and vol of the future underlying prices
- future drift and vol = past drift and vol
- macroeconomic context: future = past
- no dividends in the underlying
- no stock splits
- no discounting
- the KPI is the accounting P/L
- the implemented algo only supports closing prices - no candlesticks, no moving averages
- no public holidays in the simulated future prices
- unlimited treasury funding (...)
- no brokerage fees
- no management fees

# Risks and Contingencies

Our pricing function is not going to be linear, which implies that a huge number of stochastic simulations is required.

# Data mining goals

We want to have an environment that supports a huge number of simulations in a reasonable amount of time.

# Project plan

We are going to define the pricing function in python.
the pricing is made of a descriptive-analytics step that takes a profile of the historical prices and a predictive-analytics step that creates a number of future scenarios.
the pricing is executed on each scenario by executing the rules of different scenarios of contracts.
This is executed on the cloud.

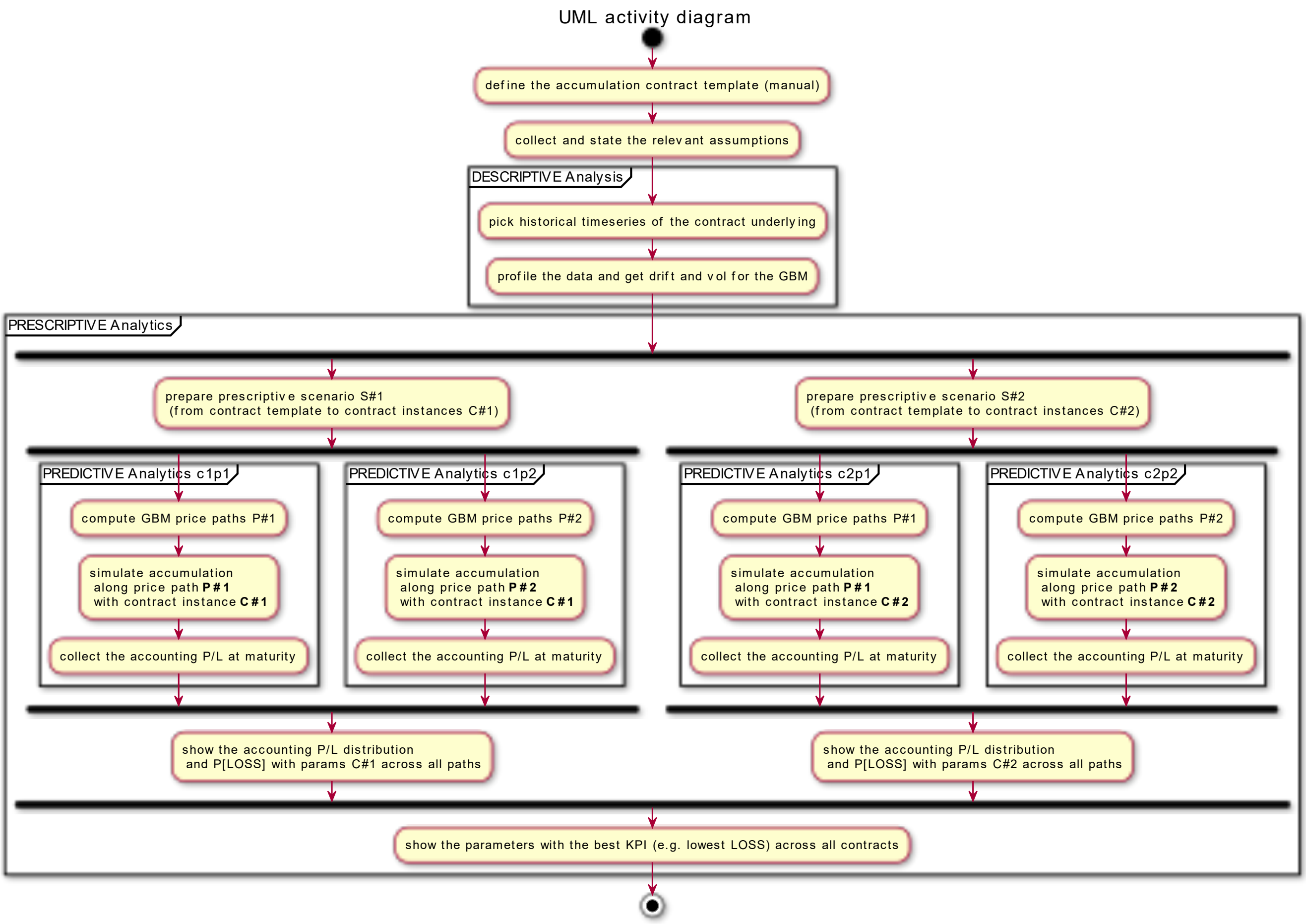
## Summary of the workflow

Below is the complete workflow, which is based on two nested iterations: the outer loop is based on a variety of contract parameters and the inner loop is based on a variety of simulated future price series.

The pseudocode is as follows:

```
# PSEUDOCODE:
for S in ContractParametersScenarios:
  for P in PricePathsNumber:
    M = HistoricalStockPrice_StatisticModel( stockPriceHistory )
    RandomPricePath = BuildRandomWalk( priceStatProfile=M )
    CONTRACT = ContractWithParameters( scenario=S )
    PNLarray[P] = computePnL(CONTRACT,RandomPricePath)
  # end of loop: for P
  Risk[S] = downsideRisk( PNLarray )
# end of loop: for S
```

The modified workflow, more performant and suitable for parallel runs, is as follows:



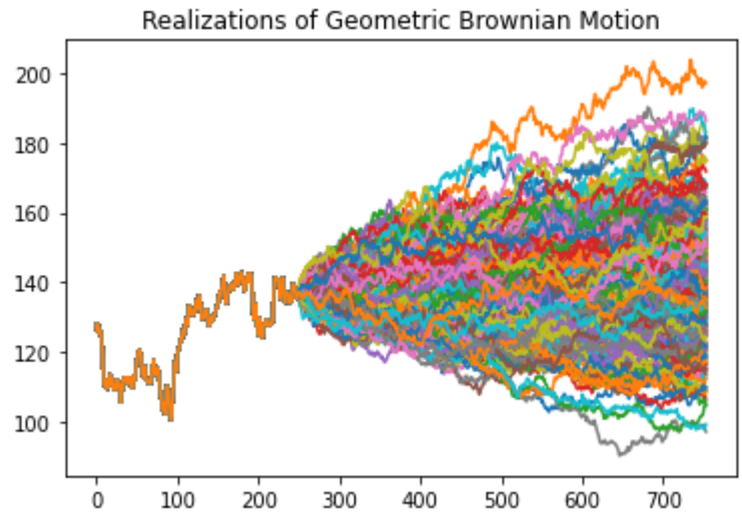

# The data

We are going to use the historical prices taken from Yahoo Finance of the JPMC on the NYSE: [https://finance.yahoo.com/quote/JPM/](https://finance.yahoo.com/quote/JPM/)

# Modeling

## The descriptive analytics sub-process

One year of historical price series of the underlying stock is analyzed; based on its statistical profiles, a high number of stochastic, two-year future price paths is computed:




(Algorithm taken from the [wikipedia page on GBM](#) and Hull, OF&OD 8th ed. §13.3)

## The predictive analytics sub-process

An example of parametric specification of the Equity Accumulator contract is below - it contains

- a reference to the underlying contract
- the algo trading rules
  - formulas that are computed dynamically
  - lookups of the historical prices of the underlying
  - variables that are the subject of our investigation - we want to find the optimum combination

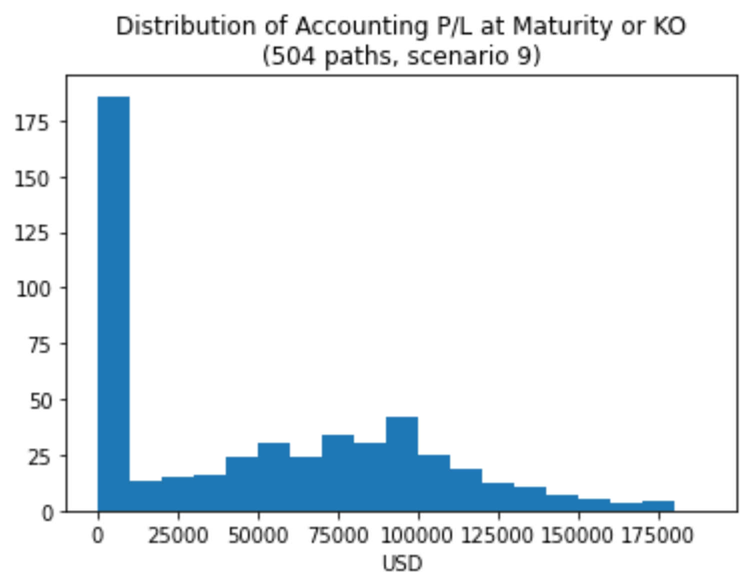
```
{
    "contract": "JPMC_NYSE",
    "file": "jpm.csv",
    "market": "NYSE",
    "desc": "...",
    "knock-in": "row.AdjClose > 145",
    "knock-out": "row.AdjClose <= 120",
    "dates": {
        "startdate": "2022-06-02",
        "enddate": "2024-05-22",
        "dateformat": "%Y-%m-%d",
        "filedateformat": "%Y-%m-%d"
    },
    "missing": "forward linear",
    "comments": [
      "BQ and SQ and PRESCRIPTIVE variables.",
      "the expressions can make use of min, max, avg, abs, math.ceil() et c
```

```
            "H is the historical time series."
        ],
        "buy": {
            "qty": "BQ",
            "at": "hist('AdjClose',T,0,H)",
            "when": "hist('AdjClose',T,0,H) > hist('AdjClose',T,-1,H)"
        },
        "sell": {
            "qty": "SQ",
            "at": "hist('AdjClose',T,0,H)",
            "when": "hist('AdjClose',T,0,H) < hist('AdjClose',T,-1,H)",
            "desc": "if 2% up or more, sell"
        }
    }
```

The buy quantity and sell quantity are parametric: "BQ" and "SQ". We will generate multiple scenarios based on random values. For our scenario #9, which comes with (BQ,SQ) = (6, 9), the distribution of the PV is as follows:

```
print('len:',len(sample_histog_data),'max:',max(path_lastCumCF))
# len: 504 max: 194444.43
pyplot.hist(path_lastCumCF, density=False, bins=[10000*i for i in range(20)]
```

### The distribution of P/L for the predicted scenario #9 : (BQ, SQ) = (6, 9)

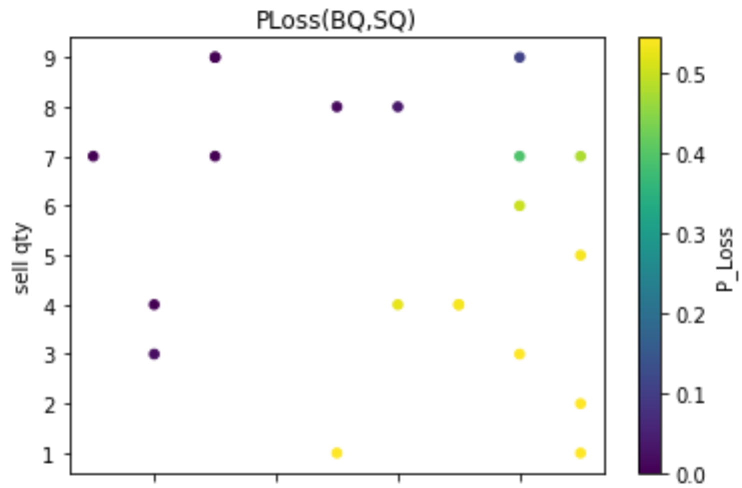



# Evaluation

## The prescriptive analytics sub-process

The optimization of our objective (i.e., minimize the probability of loss) occurred, in our simulations, with these parameters:

| BuyQty | SellQty | P(Loss) | Max CumulCashFlow | Min CumulCashFlow |
|---|---|---|---|---|
| 2 | 4 | 0.0 | 50121.17 | 0.00 |
| 3 | 9 | 0.0 | 132204.52 | 0.00 |
| 1 | 7 | 0.0 | 120098.53 | 0.00 |
| 3 | 7 | 0.0 | 94189.34 | 0.00 |
| 3 | 9 | 0.0 | 132204.52 | 0.00 |




# Deployment

The python notebook (code and charts), is available at this [link](link)

The code ready for Ray parallel runs is available at this [link](link)

## Fitting the desktop code into a parallel computing framework

> The non-parallel execution of **6** prescriptive scenarios,
> each with 504 2-year stochastic future price paths,
> takes approximately **2 hours 30 minutes** on an **AWS t2.micro EC2** instance.

The same code, having most of the computation that is an embarassingly parallel workload, can be **easily transformed in a parallel code that sits on top of the python Ray framework** and its Futures.
The same can be seamlessly deployed on **AWS Glue** that, since 2023, supports Ray in a few regions.

The list of the modifications to the python code are as follows:

lines added:

```
# GLUERAY
import ray
ray.init('auto')
```

decoration added in the function that runs as a parallel task, which is:
*apply the financial contract rules (the version with the parameters defined by scenario S) to one 2-year future path price P*

```
# GLUERAY
# By adding the `@ray.remote` decorator, a regular Python function
# becomes a Ray remote function.
@ray.remote
def get_remote_task_result(acchist_stats_dict,contract_dict,noFutprices,scn)
```

function execution modification:

```
# GLUERAY

# non-Ray:
# scn_lastCumCF_array = [ get_remote_task_result(acchist.stats,contract_dict

    # with Ray:
scn_lastCumCF_array_futs = [ get_remote_task_result.remote(acchist.stats,con
scn_lastCumCF_array = ray.get(scn_lastCumCF_array_futs) # = waitAll API
```

The modified python script, wrapped in a glue job that we call "ray_kiko1", is executed with the following AWS CLI command:

```
aws glue start-job-run --job-name ray_kiko1 --number-of-workers 8 --worker-t
```

> The parallel execution of **20** prescriptive scenarios,
> each with 504 2-year stochastic future price paths,
> takes approximately **6 minutes** - of which 30 sec for start-up - with the 8 workers provided (16 DPUs). Cost = USD 0.74 (updated 2023)

*NB - the program is designed as a serial execution of scenarios that include the paraller evaluation of the 504 price paths.*

The telemetry is implemented as calls to an instance of nginx:
server:

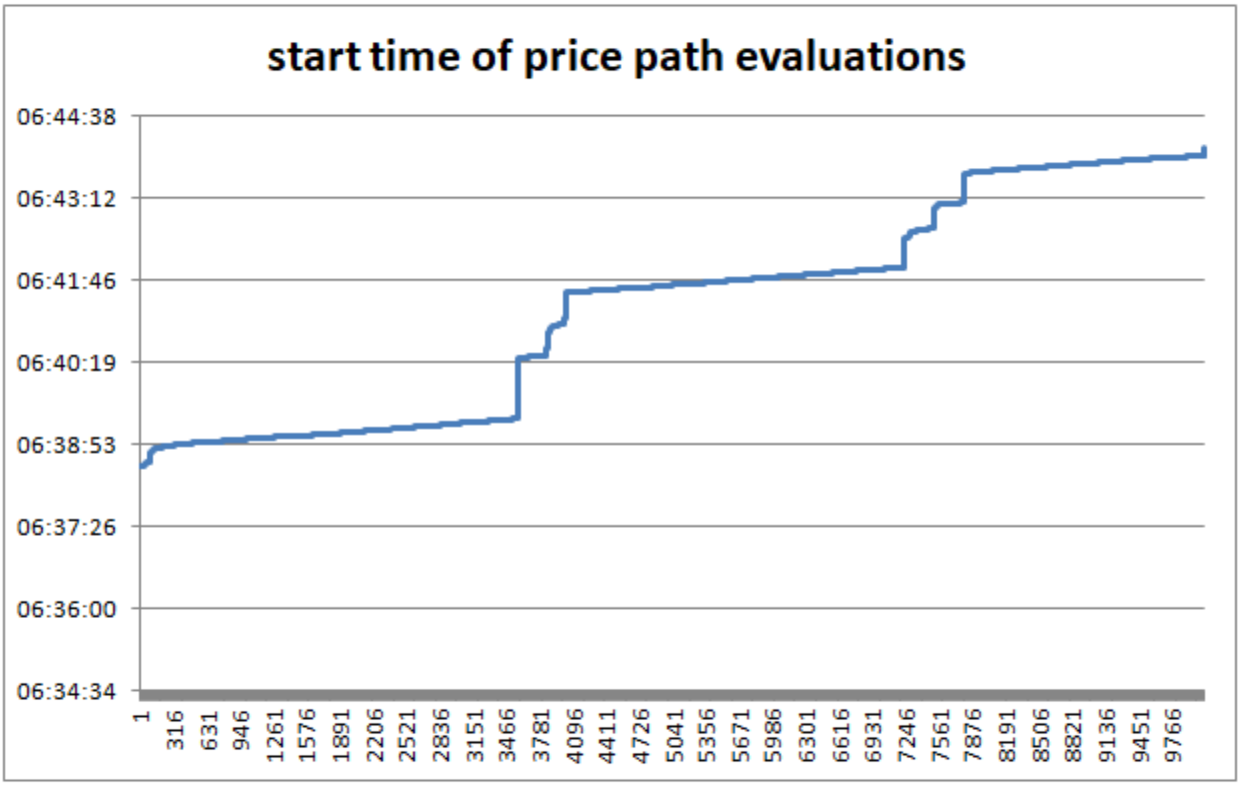
```
image: "nginx:latest"
```

nginx.conf

```
log_format  main '$time_local;$time_iso8601;$remote_addr;$status;$request';
```

python client:

```
payload={'tag':tag,'scenario':scenario,'pxpath':pxpath}
response = requests.head(http://aws-ec2-url/log, params=payload)
```



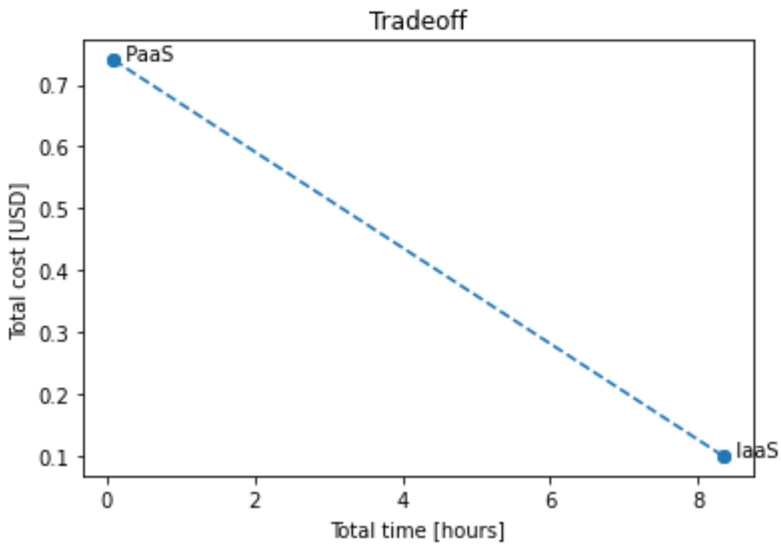

## Cost/time tradeoff

| service | computed scenarios | cost/hour | cost/job | hours | total cost |
|---|---|---|---|---|---|
| IaaS (AWS EC2) | 6 | 0.0116 | N/A | 2.50 | 0.03 |
| IaaS (AWS EC2) (projection) | 20 | 0.0116 | | 8.33 | 0.10 |

| service | computed scenarios | cost/hour | cost/job | hours | total cost |
| --- | --- | --- | --- | --- | --- |
| Paas (AWS Glue) | 20 | N/A | 0.74 | 0.10 | 0.74 |

*Costs in USD 2023*

*NB no lead time is included in EC2 calculations (EC2 setup time and final 'reduce' step takes less than 1 min)*




# Appendix

## Relevant AWS and Ray links

- https://www.ray.io/
- https://docs.aws.amazon.com/glue/latest/dg/author-job-ray-job-parameters.html
- https://docs.aws.amazon.com/cli/latest/reference/glue/start-job-run.html
- https://docs.aws.amazon.com/glue/latest/dg/ray-jobs-section.html#author-job-ray-worker-accounting
- https://d1.awsstatic.com/events/Summits/reinvent2022/ANT343_Build-scalable-Python-jobs-with-AWS-Glue-for-Ray.pdf

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