Monte Carlo Scheduler

Predicting duration for completion of future tasks based on knowledge estimates from historical data

This simple program utilises a primitive linear regression model for prediction of actual time for completion of tasks based on the estimates provided by randomly sampling data from historical records to run a simulation over n iterations, resulting in a list of predictions grouped with their count of occurences from which confidence values can be computed for each prediction. Thus in a typical Monte Carlo Simulation, greater the confidence, greater becomes the probability for better prediction and greater the number of trials, greater becomes the accuracy.

Sample Datasets used for this Simulation

```
import pandas as pd
print("HISTORICAL TASK DATA")
print(pd.read_csv('historical.csv'))
print()
print("FUTURE TASK DATA")
print(pd.read_csv('future.csv'))
```

```
HISTORICAL TASK DATA
   Task Name  Estimate  Actual
0     Task 1        10      12
1     Task 2         8      12
2     Task 3        10      16
3     Task 4         8      10
4     Task 5         8      16
5     Task 6         8      14
6     Task 7        12      16
7     Task 8        16      24
8     Task 9         8      16
9    task 10        12      24
10   task 11        20      24
11   task 12        14      20
12   task 13         8      10
13   task 14        12      14
14   task 15        16      12
15   task 16        20      24
16   task 17         8      12
17   task 18        12      12
18   task 19        24      26
19   task 20        20      24
20  Task 21"        16      16
21   task 22         8       9
22   task 23        20      23
23   task 24         8       8
```

```
FUTURE TASK DATA
   Task Name  Estimate
0      Task 1         2
1      Task 2        19
2      Task 3         2
3      Task 4        11
4      Task 5        32
5      Task 6         3
6      Task 7         2
7      Task 8         4
8      Task 9        33
9     Task 10        20
10    Task 11        19
11    Task 12         7
12    Task 13        31
13    Task 14         3
14    Task 15         8
15    Task 16        20
16    Task 17         2
17    Task 18         3
18    Task 19        19
19    Task 20        19
20    Task 21         3
21    Task 22         6
22    Task 23         7
23    Task 24        18
24    Task 25         2
25    Task 26        11
26    Task 27        18
27    Task 28        10
28    Task 29         3
29    Task 30        32
30    Task 31         2
31    Task 32         6
```

Imports

```
import csv
import math
from random import *
from matplotlib.pyplot import *
```

Loading the Datasets

The CSV files for the scheduling task is loaded by the following function, which generalises the loading and parsing of .csv files into nested list of records, better suited for data transformation and manipulation. `Pandas.read_csv()` can also be used to do the same.

```
# CSV LOADER
def loadCSV(filename):
    hasHeaders=False
    with open(filename) as csvfile:
        output = []
        # sample head buffer to explore .csv paramaters
        sample = csvfile.read(1024)
        # check if .csv has headers
        hasHeaders = csv.Sniffer().has_header(sample)
        # get encoding parameters in .csv
        dialect = csv.Sniffer().sniff(sample)
        # move cursor to start of .csv
        csvfile.seek(0)
        # begin reading .csv with scanned parameters
        reader = csv.reader(csvfile,dialect)
        # skip the header row in .csv
        firstLine = True
        for row in reader:
            if (hasHeaders and firstLine):
                firstLine = False
            else:
                # parse each record based on type
                record = []
                for col in row:
                    if col.isnumeric():
                        record.append(int(col))
                    else:
                        record.append(col)
                # append parsed record to output
                output.append(record)
        return (output)
# DATASET LOADER
def loadData(historicalFilename, futureFilename):
    historical   = loadCSV(historicalFilename)
    future               = loadCSV(futureFilename)
    hasHeaders=False
    return(historical, future)
```

Running the Simulations

Monte Carlo Method

A Monte Carlo Simulation is a way of approximating the value of a function where calculating the actual value is difficult or impossible. It uses random sampling to define constraints on the value and then makes a sort of "best guess."
It works by the ***Principle of Large Numbers*** *which states that*

"As the number of identically distributed, randomly generated variables increases, their sample mean (average) approaches their theoretical mean."

The functions for carrying out these simulations are elaborated below.

Simulator Functions

Function to run *one* simulation.
Mathematically, it computes the following expression.

$$\left(\frac{sample(history)_{actual}}{sample(history)_{estimated}}\right) \times future_{estimated}$$

```
Runs 1 simulation of future data based on historical data.
Input:  historical      = list of lists in the format: [[TaskName, estimated, actual],
...]
        future          = list of lists in the format: [[TaskName, estimated], ...]


def runSimulation(historical,future):
    predictedTotal=0
    for task in future:
        selectedEvent = historical[randint(0,len(historical)-1)]
        velocity = selectedEvent[2]/selectedEvent[1]
        predicted = velocity*task[1]
        predictedTotal+=predicted
        task.append(predicted)
    predictedTotal=round(predictedTotal,2)
    return (predictedTotal)
```

Function to run N simulations.

```
Runs n simulations of future data based on historical data.
Input:  historical      = list of lists in the format: [[TaskName, estimated, actual],
...]
        future          = list of lists in the format: [[TaskName, estimated], ...]
        n                        = number of simulations to run


def runSimulations(historical,future,n=1,verbose=False):
    estTotal=0
    predictions=[]
    for task in future:
        estTotal+=task[1]
    print("Total Hours Estimated: "+str(estTotal))
    for i in range(0,n):
        predictedTotal = runSimulation(historical,future)
        predictions.append(predictedTotal)
        if (verbose):
            print ("Trial {0:2} prediction: {1:.0f} ({2:.2f}% of
```

```
estimated)".format(i,predictedTotal,100*predictedTotal/estTotal))
    print("Takes a Minimum of {0:.0f} hours for all tasks to complete. ({1:.2f}% of
estimated hours)".format(min(predictions),100*min(predictions)/estTotal))
    print("Takes a Maximum of {0:.0f} hours for all tasks to complete. ({1:.2f}% of
estimated hours)\n".format(max(predictions),100*max(predictions)/estTotal))
    return(sorted(predictions))
```

Functions for Probablistic Conversion

These functions count for the probability of occurence of each prediction, which is later used for plotting the predictions against the perfect estimate as the confidence reaches its peak (*i.e. Simulations completed nears the value of* N)

Summarize Function

```
Input: List of predictions
Output: Nested lists of prediction and their count
```

```
def summarize(data):
    points = []
    output=[]
    for p in data:
        if (p not in points):
            points.append(p)
    for p in points:
        c = data.count(p)
        output.append([p,c])
    return(output)
```

Confidence Computing Function

```
Input: Prediction counts, nested lists of format [[prediction, count],...]
Output: Predictions with confidence percentages of format [[prediction, percent],...]
```

```
def computeConfidence(data,verbose=False):
    trialsSoFar=0
    totalTrials = sum([predWithTrials[1] for predWithTrials in data])
    if (verbose):
        print("Total trials: {0}".format(totalTrials))
    confidenceRatings=[]
    for prediction in data:
        trialsSoFar+=prediction[1]
        confidence = float(trialsSoFar)/float(totalTrials)*100
        if (verbose):
            print("Prediction: {0} (Confidence:
{1:.2f}%)".format(prediction[0],confidence))
        confidenceRatings.append([prediction[0],confidence])
    return(confidenceRatings)
```

Model Runner

```
Input: Historical and Future data
Output: Ascending Ordered Predictions with confidence in format: [[predicted,
confidence percent],...]
        (Interpreted as "C% completion chance for P")


# MODEL RUNNER FROM FILE (STEP--1)
def runModelFromFiles(historicalFilename,futureFilename,trials=10000,plot=True):
    historical, future  = loadData(historicalFilename,futureFilename)
    return runModelFromData(historical,future,trials,plot)
# MODEL RUNNER FROM DATA (STEP--2)
def runModelFromData(historical,future,trials=10000,plot=False):
    print("Running {0} trials.".format(trials))
    matplotlib.pyplot.clf()
    simulationData              = runSimulations(historical, future,trials)
    summaryData                 = summarize(simulationData)
    confidenceData              = computeConfidence(summaryData)
    perfectEstimate = sum([item[1] for item in future])
    if (plot == True):
        plotPredictions(confidenceData,perfectEstimate)
    return(confidenceData,perfectEstimate)
```

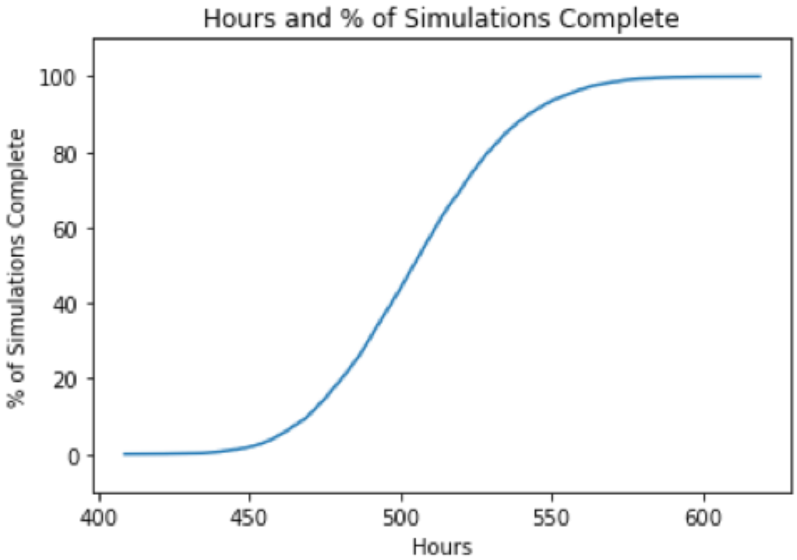
Model Plotter

```
def plotPredictions(confidenceData,estimated=None,xLabel="Hours",yLabel="% of
Simulations Complete",chartType="plot"):
    x = [item[0] for item in confidenceData]
    y = [item[1] for item in confidenceData]
    matplotlib.pyplot.title('{0} and {1}'.format(xLabel,yLabel))
    if (len(y)<10):
        lefts = [v-.5 for v in x]
        matplotlib.pyplot.ylim(0,110)
        matplotlib.pyplot.bar(lefts,y,width=((max(x)-min(x))/(len(x)-1)))
        if (estimated is not None):
            x.append(estimated)
        matplotlib.pyplot.xticks(x)
    else:
        matplotlib.pyplot.ylim(-10,110)
        matplotlib.pyplot.plot(x,y)
    matplotlib.pyplot.xlabel(xLabel)
    matplotlib.pyplot.ylabel(yLabel)
    matplotlib.pyplot.show()
```

Model Execution

```
def main():
    runModelFromFiles('historical.csv','future.csv')
main()
```

```
Running 10000 trials.
Total Hours Estimated: 377
Takes a Minimum of 409 hours for all tasks to complete. (108.43% of estimated hours)
Takes a Maximum of 619 hours for all tasks to complete. (164.15% of estimated hours)
```



png

Arvind Srinivasan. 2019.