GYASI BAWUAH, MBA, MS.

(C) 469-315-4951 (E) kgbawuah@yahoo.com

- *Open to Relocation and can travel more than 50% of the time.*

Summary of Skills:

Machine Learning Algorithms, Data Visualization with Tableau, Data Analytics

- ❖ Using Tableau to create action driven, meaningful, and insightful reports and dashboards that tell a complete story about a set of data, while identifying trends and opportunities to support business strategy and competitive advantage.
- ❖ Using R statistical software to perform time series forecasting analytics, developing models that give perspectives about future expectations, and eliminating/minimizing guess works that may have financial implications.
- ❖ Using Python programing to develop predictive models to determine the likelihood of future outcomes based on historical, internal or external data.
- ❖ Using Python for text mining and Natural Learning Processing (NLP) to mine or transform unstructured texts and blending with structured data to provide insights and analysis.
- ❖ Using IBM Cognos Report Studio to create, distribute, and automate a wide range of professional reports.
- ❖ Coordinating with and working closely with different experts to undertake business projects.
- ❖ Analyzing complex business problems, researching them, and providing intelligent suggestions, and recommendations.
- ❖ Making presentations to higher officials, peers, and large audiences.

Job History

Data Analyst

American Century Investments (Contractor), Kansas City, MO: October 2017 – Present

Resources: Tableau, Microsoft Access, R, Python, SQL, Microsoft Excel.

- ❖ Used Tableau to develop automated versions of our daily, weekly, and monthly Net Investment reports for company-wide distributions, cutting down production time and manual validations which frequently led to errors.
- ❖ Led an initiative to develop and maintain time series forecasting models to statistically approximate our monthly and year-end Net Investment performances to aid financial planning, and product development.
- ❖ Developed and maintains quarterly performance dashboards for town hall meetings.
- ❖ Developed and maintains executive dashboards for Board of Directors in Kansas City (MO), Mountain View (CA).
- ❖ Developed and maintains Month in Review (MIR) reports and commentaries that are distributed to Board of Directors, Executive Management, and all managers.
- ❖ Redesigns Excel or SAS based reports into visually appealing and interactive dashboards in Tableau.
- ❖ Research data trends and variations in business metrics to provide insights, while explaining dramatic changes or outliers.
- ❖ Provide ad hoc reports to support a wide range of users across the organization.
- ❖ Leading an initiative to develop a predictive model using internal and external data to explain factors that can determine whether the annual Net Investment would be positive or negative.

HR Analyst

Sprint Connect LLC, Overland Park, KS: January 2017 – September 2017

Resources: Tableau, R, Python, IBM Cognos, Microsoft Excel, UltiPro.

- ❖ Managed the Human Resource Information System (HRIS).
- ❖ Performed daily and weekly audits on employees' time card records and liaised with managers and the payroll team to address actual or potential pay errors.
- ❖ Developed employee headcount dashboards and time-off reports to provide the HR Vice President with daily/weekly/monthly state of the business.
- ❖ Developed Time & Attendance and payroll reports that were distributed to the payroll team and all managers across the organization.
- ❖ Developed store-level performance reports and dashboards that were distributed to the operations team and all store managers across our 15 business States.
- ❖ Led an initiative to develop a predictive model that explained critical factors that were causing our high attrition rate, to help HR reform its hiring, reward and compensation policies.
- ❖ Led an initiative to design and implement workflow systems that streamlined the company's time-off requests, hiring, terminations, and changes.
- ❖ Led an initiative to develop a fraud-detection report that targeted certain non-exempt employees who were gaming the Time & Attendance system.
- ❖ Troubleshot the Time & Attendance system for employees.

HR Support Specialist

Waddell & Reed, Mission, KS: December 2015 – December 2016

Resources: Tableau, IBM Cognos, Microsoft Excel.

- ❖ Supported the management of the Human Resource Information System (HRIS).
- ❖ Performed daily and weekly audits on employees' time card records and liaised with managers and the payroll team to address actual or potential pay errors.
- ❖ Maintained employee master data for over 1000 employees and contractors.
- ❖ Provided ad hoc reports for all managers across the organization.
- ❖ Provided the benefits teams with employee enrolment reports and open-enrolment activities.
- ❖ Developed employee headcount, hiring, changes, and termination dashboards and reports for HR.
- ❖ Developed training documents for all managers and non-managers.
- ❖ Troubleshot the Time & Attendance system for employees.

Training & Development Consultant

TriWest Healthcare Alliance (Contractor), Olathe, KS: September 2015 – December 2015

- ❖ Led with a team that set up new business locations in Kansas City, Nashville, and Sacramento. Provided health insurance and technology training to new employees.
- ❖ Developed training and evaluation materials.

Training & Development Consultant

Convergys Corporations, Olathe, KS: September 2013 – August 2015

- ❖ Provided health insurance and technology training to new and existing employees.
- ❖ Developed training and evaluation materials.

Data Analyst

Government of Ghana, Ghana, MO: May 2011 – December 2012

Resources: SPSS, Microsoft Excel.

- Created HR dashboard to help the Director of HR monitor employee headcount.
- Developed employee attendance reports for 27 agencies and departments.
- Supported Finance with planning and forecasting models and analytics.
- Maintained employee master data for over 1000 employees.
- Provided all directors and supervisors with ad hoc fund management reports.

Education

Master of Science: Business Intelligence & Data Analytics

Rockhurst University- May 2018.

Master of Business Administration (MBA): Management Information Systems & Quality Management

Park University- December 2016.

Bachelor of Arts (BA): Psychology

University of Ghana- May 2011.

Sample Projects Attached:

- Tableau Dashboards
- R Statistical Software: Forecasting Analytics
- Python Programming: Modeling

Gyasi Bawuah
Data/Report Analyst

Top 10 Clients

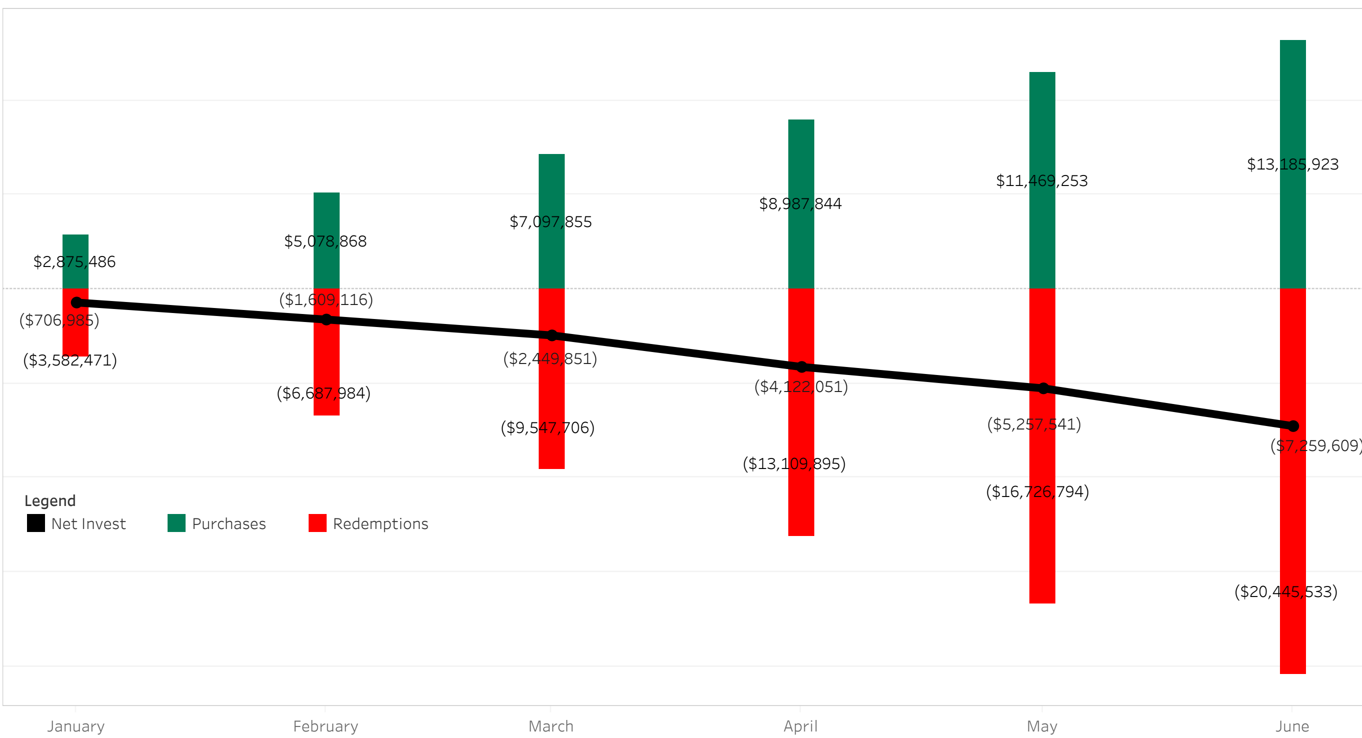
Company ID	
394,723,802	$11,918,761
148,292,437	$10,693,252
806,109,666	$9,975,611
292,727,559	$8,619,378
953,794,907	$6,691,345
200,752,288	$4,745,940
496,024,876	$4,437,249
488,508,343	$4,163,255
632,027,447	$3,241,054
296,690,464	$2,935,620

Top 10 Clients' Assets as a % of Total Asset

Top10_AUM	Total AUM	
$67,421,464	$134,274,017	50.2%

	Redemption Rate	Purchase Rate
2014	-23.2%	20.8%
2015	-20.8%	20.9%
2016	-22.1%	22.8%
2017	-22.5%	16.9%
2018	-17.3%	11.8%

Complex



Sales Strategy

Sales Strategy	
ONE CHOICE TARGET DATE	$23,274,788
GLOBAL GROWTH STRATEGIES	$17,534,166
U.S. VALUE YIELD	$14,016,188
U.S. PREMIER LARGE CAP GROWTH STRATEGIES	$12,378,032
U.S. MID CAP VALUE	$11,048,673
U.S. LARGE CAP GROWTH	$8,211,699
ONE CHOICE TARGET RISK	$5,312,317
U.S. CORE FIXED INCOME STRATEGIES	$5,200,009
NON-U.S. GROWTH STRATEGIES	$5,164,455
U.S. OPPORTUNISTIC MID CAP GROWTH	$5,051,352

Marketing Disc

Marketing Discipline	
Multi-Asset Strategies	$36,448,383
Global Value	$34,419,983
U.S. Growth	$32,678,832
Global & Non-U.S. Growth	$29,464,702
Bond	$24,084,799
Disciplined Equity	$6,830,149
Money Market	$4,055,326
AC Alternatives	$873,420
AC ETFs	$19,065

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BY CHANNEL - WEEKLY

Channel	Sub Channel	Purchases	Redemptions	Net Investment	Acquisitions	Exch/Tran	Net Flows	AUM
DIRECT	MONEY MARKET	15,165	(16,373)	(1,209)	0	3,112	1,903	3,610,949
	LONG TERM	18,396	(29,514)	(11,117)	0	(14,696)	(25,813)	36,203,424
SUB TOTAL		33,561	(45,887)	(12,326)	0	(11,584)	(23,910)	39,814,373
INTERMEDIARY	BANKS	16,511	(49,930)	(33,419)	0	(252)	(33,671)	5,246,762
	INDEPENDENT RECORDKEEPERS	43,088	(83,582)	(40,494)	0	0	(40,494)	7,153,193
	INSURANCE COMPANIES	92,535	(322,820)	(230,285)	0	(263)	(230,547)	27,394,321
	MULTI CHANNEL FIRMS	129,579	(315,939)	(186,360)	0	4,502	(181,858)	39,257,665
	WEALTH MANAGERS	78,162	(113,737)	(35,574)	0	4,627	(30,947)	24,157,534
SUB TOTAL		359,875	(886,008)	(526,133)	0	8,614	(517,518)	103,209,474
GLOBAL INSTITUTIONAL	APAC	4	(563)	(559)	0	0	(559)	4,883,780
	EMEA	0	(1,274)	(1,274)	0	0	(1,274)	11,598,673
	NOMURA	967	(6,790)	(5,824)	0	0	(5,824)	1,405,597
	NORTH AMERICA INSTITUTIONAL	8,634	(38,775)	(30,140)	0	0	(30,140)	9,153,058
SUB TOTAL		9,605	(47,402)	(37,797)	0	0	(37,797)	27,041,107
CORPORATE MONEY		16,906	(15)	16,891	0	4	16,895	542,760
GRAND TOTAL		419,947	(979,312)	(559,365)	0	(2,965)	(562,330)	170,607,715

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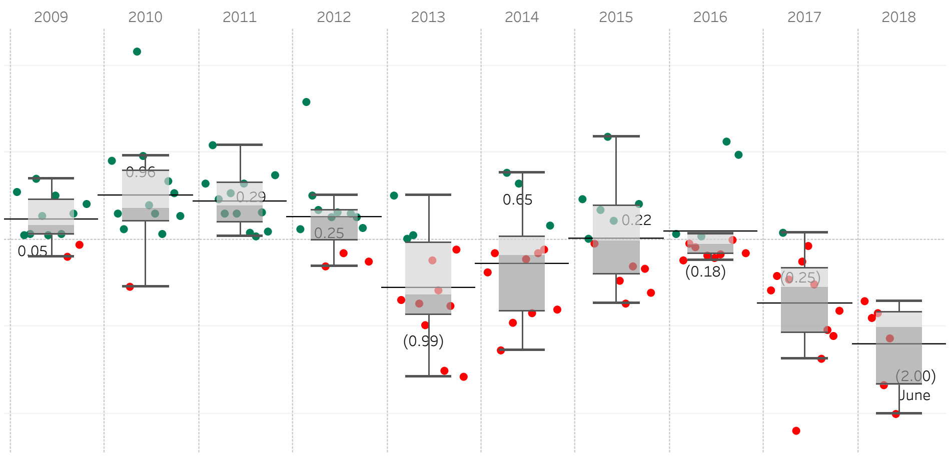
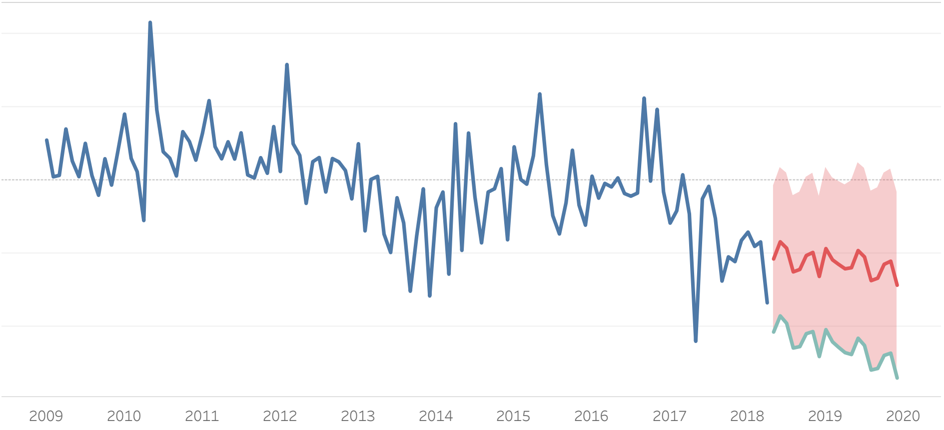
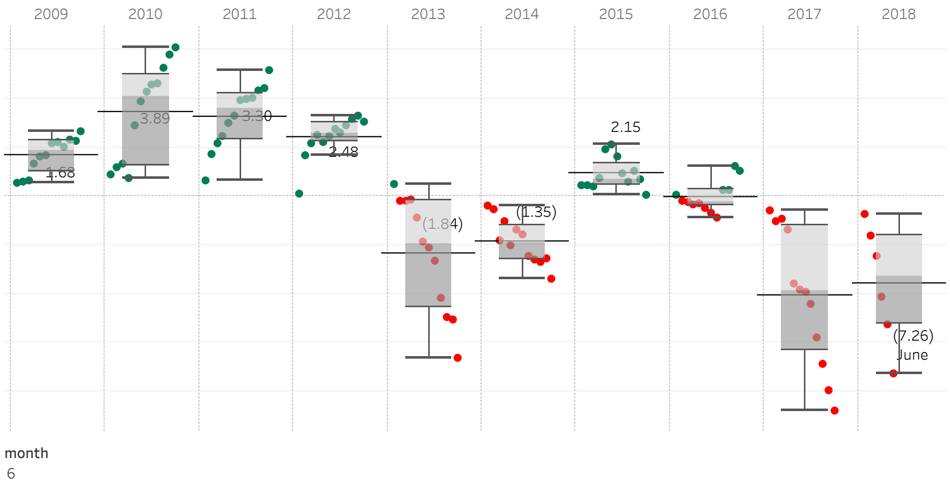
Monthly Net Investment Performance



Monthly Net Investment Forecast



YTD Net Investment Performance:January to December



YTD Net Investment Forecast

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WEEKLY NET INVESTMENT REPORT

Report as of July 8, 2018
(in thousands)

Net Investment For Week Ending:

July 8, 2018	**($576,256)**

Net Investment Through July 11, 2018

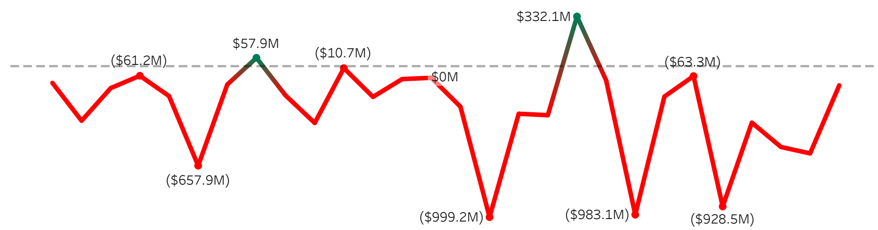
WEEK TO DATE	**($701,304)**
MONTH TO DATE	**($701,304)**
QUARTER TO DATE.	**($701,304)**
YEAR TO DATE	**($7,960,913)**

Top Positive Weeks

1	May 07, 2018	$332,095
2	February 19, 2018	$57,852

Top Negative Weeks

1	April 16, 2018	($999,214)
2	May 21, 2018	($983,059)
3	June 11, 2018	($928,474)
4	February 05, 2018	($657,905)
5	July 02, 2018	($576,256)



Number of Weeks

Positives	2
Negatives	26
Total	28

TOP CLIENTS BY STRATEGY: July 8, 2018

268508315	ONE CHOICE TARGET DATE	$14,677
148292437	EMERGING MARKETS	$13,899
148292437	U.S. LARGE CAP VALUE	$8,824
953794907	NON-U.S. GROWTH STRATEGIES	$7,305
496024876	U.S. SMALL CAP VALUE	$6,667
148292437	U.S. REAL ESTATE SECURITIES	$5,857
292727559	EMERGING MARKETS	$5,350

BOTTOM CLIENTS BY STRATEGY: July 8, 2018

792249262	U.S. LARGE CAP GROWTH	($153,714)
148292437	U.S. DISCIPLINED LARGE CAP CORE STR..	($54,017)
148292437	U.S. LARGE CAP GROWTH	($47,545)
188584208	ONE CHOICE TARGET DATE	($44,345)
148292437	U.S. VALUE YIELD	($29,771)
148292437	ONE CHOICE TARGET DATE	($25,045)
394723802	U.S. VALUE YIELD	($21,263)
923757791	NON-U.S. CONCENTRATED GROWTH ST..	($21,000)
582328309	ONE CHOICE TARGET DATE	($14,109)
200752288	ONE CHOICE TARGET DATE	($13,293)
212762832	NON-U.S. AGGREGATE FIXED INCOME	($12,384)
292727559	U.S. CORE PLUS FIXED INCOME	($10,720)
394723802	U.S. BALANCED - CORE - 60-40 STRATEGI..	($8,891)
488508343	U.S. MID CAP VALUE	($7,663)
141544804	U.S. VALUE STRATEGIES	($7,102)
900997905	U.S. MID CAP VALUE	($7,100)
141544804	ONE CHOICE TARGET DATE	($6,364)
582328309	U.S. OPPORTUNISTIC MID CAP GROWTH	($6,090)
953794907	U.S. VALUE YIELD	($5,468)
272138297	ONE CHOICE TARGET DATE	($5,430)
697186470	U.S. VALUE YIELD	($5,348)
697186470	ONE CHOICE TARGET DATE	($5,161)

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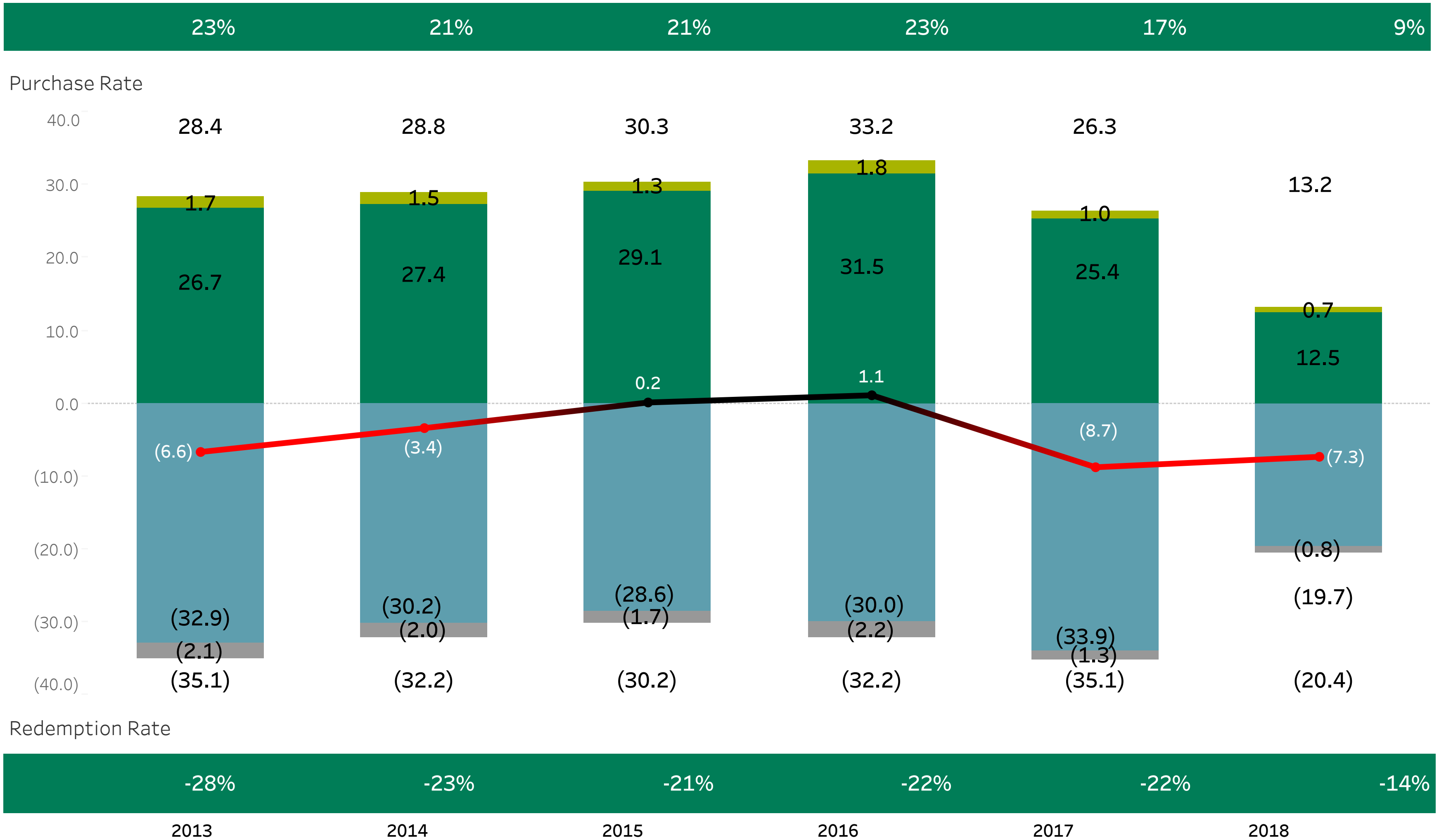
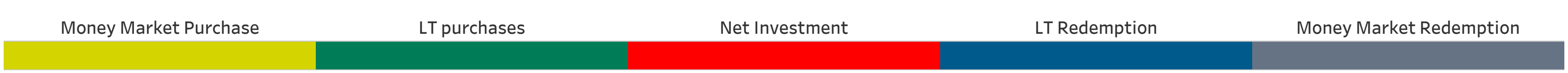
Complex Long Term ($B)



Legend



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Business Problem:

```
## Determining Factors That Can Predict Future Net Investments
```

Importing Libraries

In [2]:
```
import pandas as pd
import numpy as np
from sklearn import preprocessing
import matplotlib.pyplot as plt
plt.rc("font", size=14)
from sklearn.linear_model import LogisticRegression
from sklearn.cross_validation import train_test_split
import seaborn as sns
sns.set(style="white")
sns.set(style="whitegrid", color_codes=True)

import warnings
warnings.simplefilter('ignore', DeprecationWarning)
```

Reading data and viewing last 5 rows

In [3]:
```
data = pd.read_excel('data_pred2.xlsx', header=0)
data.tail()
```

Out[3]:

	Net Investment	Month	Year	Company	Performance
1127	-2.731277e+08	June	2018	GRE	Negative
1128	-8.243304e+07	June	2018	MAS	Negative
1129	-1.787312e+08	June	2018	NAT	Negative
1130	-1.160424e+08	June	2018	NOR	Negative
1131	1.873374e+07	June	2018	WEL	Negative

Exploratory Data Analysis

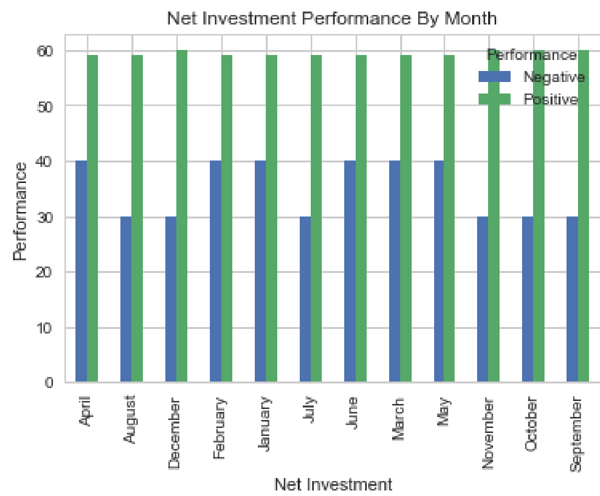
In [5]:
```
data.groupby('Company').mean()
```

Out[5]:

Company	Net Investment	Year
AME	-8.952422e+06	2013.27193
ASH	2.614420e+08	2013.27193
CAN	3.015271e+08	2013.59434
CHA	-5.611691e+07	2013.27193
FID	1.416172e+08	2013.27193
GRE	-7.925305e+07	2013.27193
MAS	7.389197e+07	2013.27193
NAT	-1.552214e+08	2013.27193
NOR	1.255051e+08	2013.27193
WEL	3.594165e+07	2013.27193

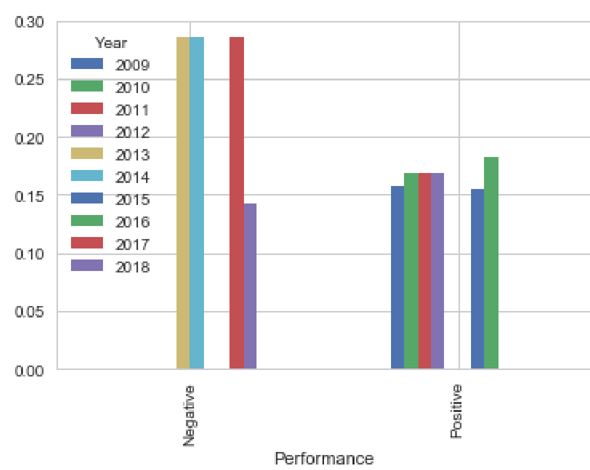
```
In [6]: %matplotlib inline
        pd.crosstab(data.Month,data.Performance).plot(kind='bar')

        plt.title('Net Investment Performance By Month')
        plt.xlabel('Net Investment')
        plt.ylabel('Performance')
```

```
Out[6]: Text(0,0.5,'Performance')
```

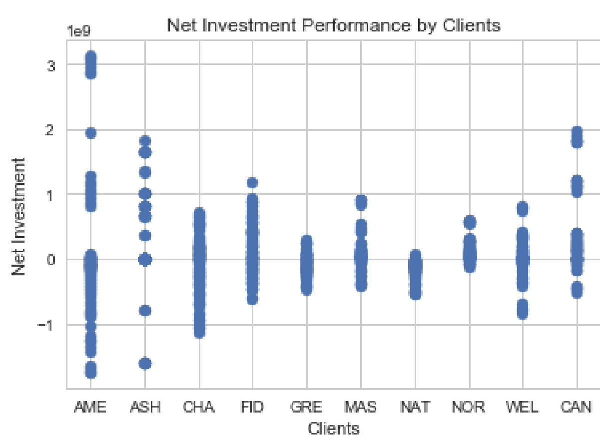



```
In [9]: table=pd.crosstab(data.Performance,data.Year)
        table.div(table.sum(1).astype(float), axis=0).plot(kind='bar', stacked=F
        alse)
```

```
Out[9]: <matplotlib.axes._subplots.AxesSubplot at 0x1a0a9568fd0>
```




```
In [10]: plt.scatter(data.Company, data['Net Investment'])
         plt.xlabel('Clients')
         plt.ylabel('Net Investment')
         plt.title('Net Investment Performance by Clients')
         plt.show()
```



Shuffling Data

In [11]:
```
from sklearn.utils import shuffle

df = shuffle(data, random_state=0)
df.head()
```

Out[11]:

	Net Investment	Month	Year	Company	Performance
14	4.123465e+08	February	2009	MAS	Positive
957	5.615290e+07	January	2017	GRE	Negative
495	1.227206e+07	March	2013	CHA	Negative
608	-1.056607e+07	February	2014	MAS	Negative
529	-1.851401e+08	June	2013	NAT	Negative

Transforming Categorical data- Performance

In [12]:
```
from sklearn import preprocessing
le_dep = preprocessing.LabelEncoder()

df['Performance'] = le_dep.fit_transform(df['Performance'])
df.head()
```

Out[12]:

	Net Investment	Month	Year	Company	Performance
14	4.123465e+08	February	2009	MAS	1
957	5.615290e+07	January	2017	GRE	0
495	1.227206e+07	March	2013	CHA	0
608	-1.056607e+07	February	2014	MAS	0
529	-1.851401e+08	June	2013	NAT	0

Normalizing data, adding dummy variables

In [13]:
```
# perform data transformation. Creates dummies of any categorical featur
e
for col in df.columns[1:]:
    attName = col
    dType = df[col].dtype
    missing = pd.isnull(df[col]).any()
    uniqueCount = len(df[attName].value_counts(normalize=False))
    # discretize (create dummies)
    if dType == object:
        df = pd.concat([df, pd.get_dummies(df[col], prefix=col)], axis=1
)
        del df[attName]

df.shape
df.describe()
```

Out[13]:

	Net Investment	Year	Performance	Month_April	Month_August	Month_
count	1.132000e+03	1132.000000	1132.000000	1132.000000	1132.000000	1132.000
mean	6.235974e+07	2013.302120	0.628975	0.087456	0.078622	0.079505
std	5.054662e+08	2.744446	0.483293	0.282627	0.269267	0.270645
min	-1.742728e+09	2009.000000	0.000000	0.000000	0.000000	0.000000
25%	-1.123984e+08	2011.000000	0.000000	0.000000	0.000000	0.000000
50%	0.000000e+00	2013.000000	1.000000	0.000000	0.000000	0.000000
75%	1.440988e+08	2016.000000	1.000000	0.000000	0.000000	0.000000
max	3.122466e+09	2018.000000	1.000000	1.000000	1.000000	1.000000

8 rows × 25 columns

Splitting data into Training and Testing sets

In [14]:
```
X = df.iloc[:,1:]
y = df.iloc[:,0]

X_train, X_test, y_train, y_test = train_test_split(X.values, y.values,
test_size=.2, random_state=0)


print(X_train.shape)
print(X_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(905, 24)
(227, 24)
(905,)
(227,)
```

Testing for significance- General Linear Model: Linear Regression

In [16]:
```python
import statsmodels.api as sm
logit_model=sm.GLM(y,X)
result=logit_model.fit()
print(result.summary())

warnings.simplefilter('ignore', DeprecationWarning)
```

```
                 Generalized Linear Model Regression Results
==============================================================================
Dep. Variable:         Net Investment   No. Observations:                 1132
Model:                            GLM   Df Residuals:                     1109
Model Family:                Gaussian   Df Model:                           22
Link Function:               identity   Scale:            2.1237716304858653e+17
Method:                          IRLS   Log-Likelihood:                -24176.
Date:                Wed, 25 Jul 2018   Deviance:                   2.3553e+20
Time:                        02:24:02   Pearson chi2:                 2.36e+20
No. Iterations:                     2
===============================================================================
                     coef    std err          z      P>|z|      [0.025      0.975]
-------------------------------------------------------------------------------
Year           -2.938e+07   5.84e+06     -5.028      0.000   -4.08e+07   -1.79e+07
Performance     2.252e+08   3.31e+07      6.805      0.000     1.6e+08     2.9e+08
Month_April     2.684e+10   5.35e+09      5.015      0.000    1.64e+10    3.73e+10
Month_August    2.686e+10   5.35e+09      5.020      0.000    1.64e+10    3.73e+10
Month_December  2.685e+10   5.35e+09      5.018      0.000    1.64e+10    3.73e+10
Month_February  2.683e+10   5.35e+09      5.013      0.000    1.63e+10    3.73e+10
Month_January   2.682e+10   5.35e+09      5.011      0.000    1.63e+10    3.73e+10
Month_July      2.688e+10   5.35e+09      5.023      0.000    1.64e+10    3.74e+10
Month_June      2.686e+10   5.35e+09      5.018      0.000    1.64e+10    3.73e+10
Month_March     2.682e+10   5.35e+09      5.011      0.000    1.63e+10    3.73e+10
Month_May       2.684e+10   5.35e+09      5.014      0.000    1.63e+10    3.73e+10
Month_November  2.686e+10   5.35e+09      5.021      0.000    1.64e+10    3.73e+10
Month_October   2.686e+10   5.35e+09      5.020      0.000    1.64e+10    3.73e+10
Month_September 2.686e+10   5.35e+09      5.020      0.000    1.64e+10    3.73e+10
Company_AME     3.214e+10   6.42e+09      5.006      0.000    1.96e+10    4.47e+10
Company_ASH     3.241e+10   6.42e+09      5.048      0.000    1.98e+10     4.5e+10
Company_CAN     3.247e+10   6.42e+09      5.055      0.000    1.99e+10    4.51e+10
Company_CHA      3.21e+10   6.42e+09      4.998      0.000    1.95e+10    4.47e+10
Company_FID     3.229e+10   6.42e+09      5.029      0.000    1.97e+10    4.49e+10
Company_GRE     3.207e+10   6.42e+09      4.995      0.000    1.95e+10    4.47e+10
Company_MAS     3.223e+10   6.42e+09      5.019      0.000    1.96e+10    4.48e+10
Company_NAT       3.2e+10   6.42e+09      4.983      0.000    1.94e+10    4.46e+10
Company_NOR     3.228e+10   6.42e+09      5.027      0.000    1.97e+10    4.49e+10
Company_WEL     3.219e+10   6.42e+09      5.013      0.000    1.96e+10    4.48e+10
===============================================================================
```

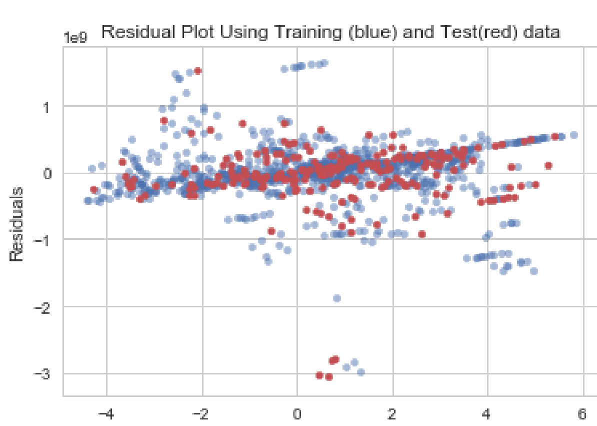
Examining Residuals

In [20]:
```python
from sklearn.linear_model import LinearRegression
```

In [21]:
```python
lm = LinearRegression().fit(X_train, y_train)
predicted = lm.predict(X_test)
```

In [22]:
```python
plt.scatter(lm.predict(X_train), lm.predict(X_train) - y_train, c='b', s
=20, alpha=.5)
plt.scatter(lm.predict(X_test), lm.predict(X_test) - y_test, c='r', s=20
)
plt.hlines(y=0, xmin=0, xmax=90)
plt.title('Residual Plot Using Training (blue) and Test(red) data')
plt.ylabel('Residuals')
```

Out[22]: `Text(0,0.5,'Residuals')`

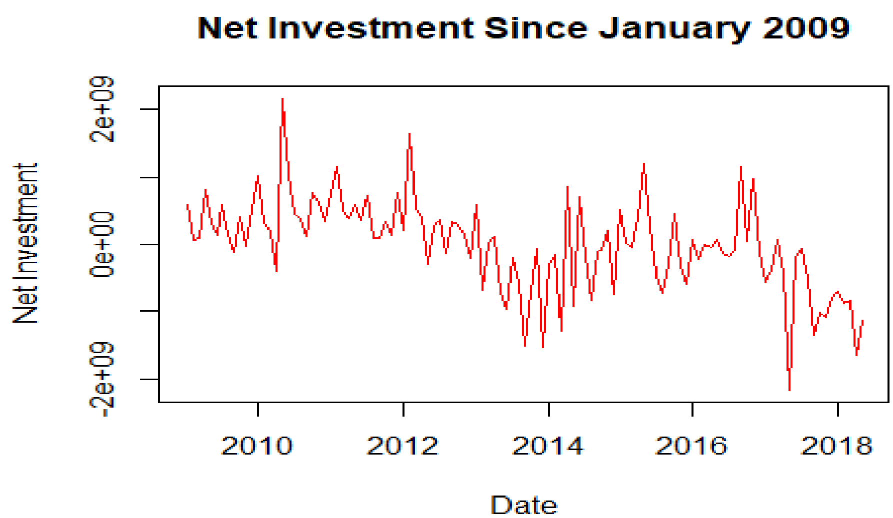


Forecasting Net Investment

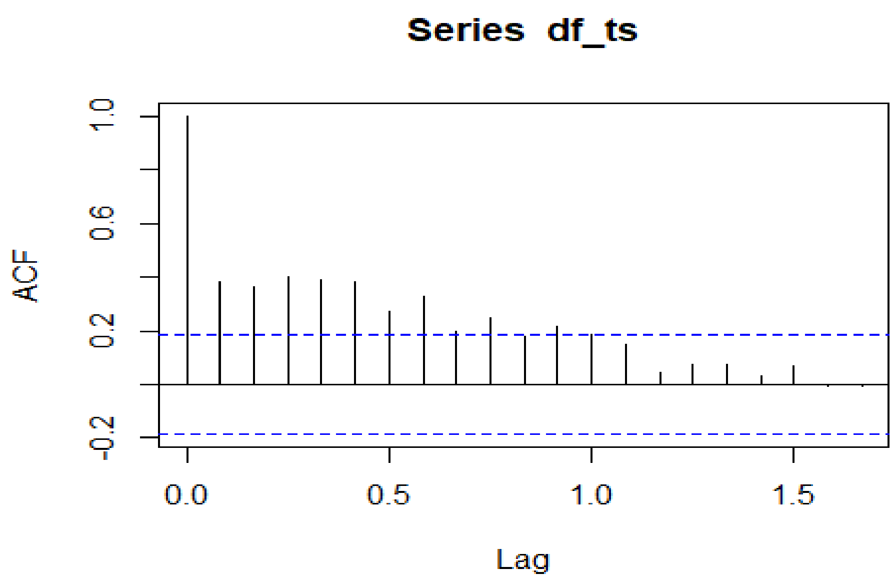
Gyasi Bawuah

June 26, 2018

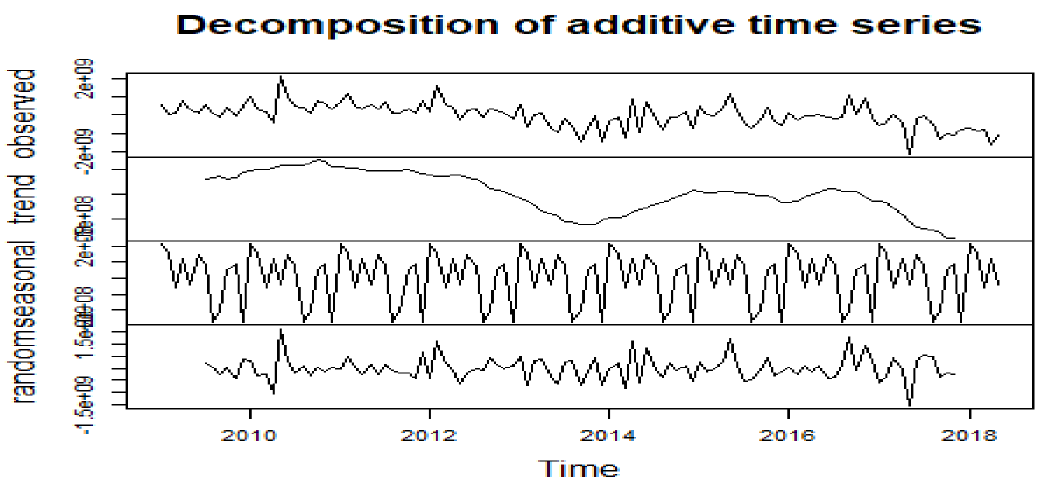
```
# Inspecting data

head(data)
## # A tibble: 6 x 2
##   period            amount
##   <chr>              <dbl>
## 1 January 2009  575813585.
## 2 February 2009  61854663.
## 3 March 2009     85156112.
## 4 April 2009    812932894.
## 5 May 2009      306970550.
## 6 June 2009     131232131.
tail(data)
## # A tibble: 6 x 2
##   period              amount
##   <chr>                <dbl>
## 1 December 2017  -785015506.
## 2 January 2018   -693605732.
## 3 February 2018  -887923022.
## 4 March 2018     -830313339.
## 5 April 2018    -1648021940.
## 6 May 2018      -1122416825.
summary(data)
##     period              amount
##  Length:113         Min.   :-2.159e+09
##  Class :character   1st Qu.:-3.931e+08
##  Mode  :character   Median : 6.185e+07
##                     Mean   :-7.665e+06
##                     3rd Qu.: 4.003e+08
##                     Max.   : 2.163e+09
# Creating Net Investment dataframe for timeseries

df = data$amount
head(df)
## [1] 575813585  61854663  85156112 812932894 306970550 131232131
# Installing and Importing Timeseries and Forecasting Libraries

library('timeSeries')
## Loading required package: timeDate
library('forecast')
# Creating Timeseries object
df_ts = ts(df, frequency = 12, start = c(2009))

plot(df_ts, main='Net Investment Since January 2009', xlab='Date', ylab='Net Investment', col=
'red')
```



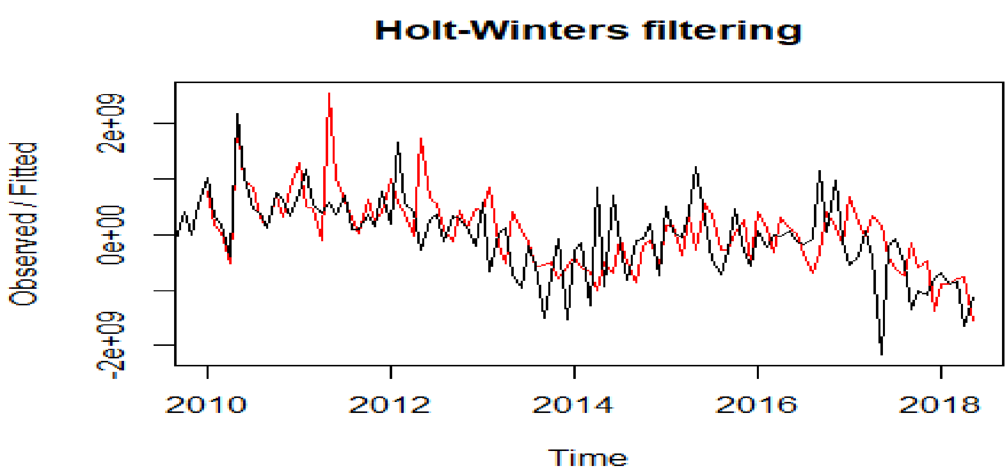

```r
# Testing Assumptions- Autocorrelation

acf(df_ts)
```



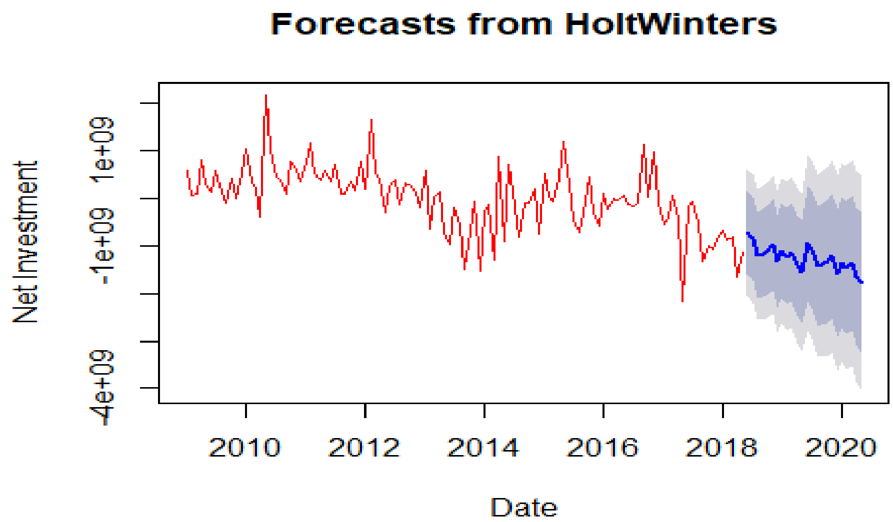

```r
# Decomposing timeseries object

decom = decompose(df_ts)
plot(decom)
```




```
#Simple Exponential Smoothing: HoltWinters

fit1 = HoltWinters(df_ts, seasonal = c('additive'))
fit1
## Holt-Winters exponential smoothing with trend and additive seasonal component.
##
## Call:
## HoltWinters(x = df_ts, seasonal = c("additive"))
##
## Smoothing parameters:
##  alpha: 0.1881403
##  beta : 0.03031403
##  gamma: 0.4325693
##

plot(fit1)
```




```
fit1$SSE
## [1] 4.695584e+19
# Ploting Forecasts

forecast1 = forecast(fit1)
plot(forecast1, col='red', xlab='Date', ylab='Net Investment')
```




```r
# Forecasting the next 12 months

head(forecast1$lower, 12)
##               80%         95%
##  [1,] -1590199105 -2051658888
##  [2,] -1734764328 -2204813917
##  [3,] -2095483053 -2574467260
##  [4,] -2082948945 -2571207837
##  [5,] -2047066308 -2544934860
##  [6,] -1934849270 -2442657079
##  [7,] -2315564519 -2833635585
##  [8,] -2109330132 -2637982684
##  [9,] -2239737711 -2779284094
## [10,] -2177504894 -2728251494
## [11,] -2471733419 -3033980633
## [12,] -2639813616 -3213855851

accuracy(forecast1)
##                     ME      RMSE       MAE       MPE     MAPE      MASE
## Training set -82528026 681842548 483011491 -55.18751 216.5697 0.7567846
##                    ACF1
## Training set -0.0777671
```