Estimation and Machine Learning Prediction of Imports of Goods in European Countries in the Period 2010-2019

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Abstract

In this article we estimate the imports of goods in European countries in the period 2010-2019 for 28 countries. We use Panel Data with Fixed Effects, Panel Data with Random Effects, Pooled OLS, WLS. Our results show that "*Imports of Goods*" is negatively associated with "*Private Consumption Expenditure at Current Prices*", "*Consumption of Fixed Capital*", and "*Gross Domestic Product*" and positively associated with "*Harmonised consumer price index*" and "*Gross Operating Surplus: Total Economy*". Finally, we compare a set of predictive models based on different machine learning techniques using RapidMiner, and we find that "*Gradient Boosted Trees*", "*Random Forest*", and "*Decision Tree*" are more efficient then "*Deep Learning*", "*Generalized Linear Model*" and "*Support Vector Machine*", in the sense of error minimization, to forecast the degree of "*Imports of Goods*".

JEL Code: *F00, F01, F02, F14, F17.*

Keywords: *General Trade, Global Outlook, International Economic Order and Integration, Empirical Studies of Trade, Trade Forecasting and Simulation.*

1. Introduction

In this article we propose an estimation of an econometric model oriented to determine the degree of "*Imports of Goods*" in European Countries in the period 2010-2019. We use data from the European Database Ameco for 28 countries[4]. Data are analyzed using Panel Data with Fixed Effects, Panel Data with Random Effects, Pooled OLS and WLS. Finally, we propose the application of different algorithm-

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based machine learning techniques to predict the degree of "*Imports of Goods*" based on the proposed econometric equation.

In role of imports in the international trade can be considered as a secondary topic since trade theory seems to be more oriented towards exports rather than imports. But, as we show in the second paragraph, the role of imports of goods is relevant, especially for low-income countries and developing countries, since it is a signal of rising GDP, increasing income per capita, and a strengthening of domestic demand. On the other side the imports of goods in high and middle-income countries have a different dynamic in respect to low-income countries. In effect in high- and middle-income countries imports of services overcome the imports of goods. Specifically, as we showed in our econometric results in the third paragraph, imports of goods in high-income countries are more associated to inputs of firm's productivity function. To better introduce the theme, we present a brief synthesis of some of the more relevant theories on international trade.

The idea of absolute advantage in Adam Smith. Adam Smith [1] introduced the idea of absolute advantage in the context of exports i.e., the idea that countries that have lower costs in producing goods are more able to sell them to other countries in the international trade. Originally, the absolute advantage was based on a unique input i.e. labor cost. The countries able to reduce labor cost was also able to win the competition to export in the context of international trade. Specifically, if a country has no possibility to reduce the cost of production, i.e., the cost of labor, then that country has more probabilities to become an importer of that good rather than an exporter. The differences among the presence of absolute advantages create a classification of countries between importers and exporters.

Ricardian theory of international trade. The economist David Ricardo [2] changed the idea from absolute advantage to comparative advantage. While Adam Smith focused only on labour, David Ricardo also considered technology and natural resources as key indicators able to evaluate the competitiveness in exports goods and services at a country level. But the Ricardian misses the evaluation of socio-economic, cultural, institutional, and environmental characteristics of the countries that can boost or reduce the productivity and the export orientation in the context of international trade. In the context of Ricardian trade theory, the role of labour-value is essential. It is necessary to understand that in the early stages of economics as a science, economists really were not able to disentangle the question of the definition of economic value especially in the form of labour-value.

The Heckscher-Ohlin model. Is a model proposed by two Swedish economists i.e., Eli Heckscher and Bertil Ohlin [3]. The Heckscher-Ohlin model is also referred as H-O model. The H-O model describes the different positions of countries in the international trade because of factor endowments. Factor endowment is the sum of a series of variables that have a role in promoting manufacturing at a regional level such as land, labor, capital, entrepreneurship, institutions, culture, language, and political economies. The differences in factor endowments explain the fact that a country is an importer or an exporter. Specifically, countries tend to export goods that make large use of factor endowments while tend to import goods that require factors that are missing at a regional level. The H-O model holds in the presence of strong assumptions i.e.:

- *Technology is country-invariant in the long run;*
- *The distribution of labor and capital differs among countries;*
- *Labor and capital flows among sectors;*
- *Consumers have similar preferences among different countries.*

The economist Wassily Leontief [4] tested the econometrically the efficacy of Heckscher-Ohlin theorem. Leontief applied the H-O theorem to the United States. The study showed that U.S. were abundant in capital and consequently based on H-O theorem U.S. should have been an exporter of capital-intensive goods. But the study showed that U.S. was net importer of capital-intensive goods. This proposition is also known as Leontief paradox.

New trade theory. Is a theory that consider the economic advantages that firms have in choosing a location that is closer to the demand. This effect is also known as home market effect. But the location in proximity with the demand market can be chosen only if the firm has returns to scales due to reduction in transportation costs [5] . This theory can sustain the political economies of imports of goods as a driver for industrialization. In effect firms that export in a country could have some economic convenience in locating their activity in the country with a significant domestic demand.

The article continues as follow: the second paragraph contains the literature review, the third paragraph presents the econometric model, the fourth paragraph indicate the predictive model, the fifth paragraph concludes.

2. Literature Review

[1] afford the question of the relationship between the quality of goods imported from German firms and the geographical distance with countries of origin. A dataset of 3.204.851 observations is analyzed in 2011, with 138.688 firms, 4.986 imported products, 1.938.602 firm-product combination, 175 countries. Results show the presence of a positive relationship between the quality of goods imported in Germany and the distance of country of origin. This positive relationship holds even after controlling for goods, firms, and firm-product.

[2] consider the positive relationship among economic growth, trade, imports and exports. Based on this assumption the authors try to estimate the level of GDP growth rate as a function of the sequent parameters:

- *Trade in services;*
- *Exports of goods and services;*
- *Imports of goods and services;*
- *Trade;*
- *Merchandise trade.*

To obtain this goal the authors use an Artificial Neural Network-ANN comparing the results of a Back Propagation learning-BP with the results of Extreme Learning Machine-ELM. Results show that the accuracy of ELM is more efficient in predicting Gross Domestic Product growth rate.

[3] afford the question of geographical determination of the imports in the Republic of Belarus. The authors have realized a comparison of imports using statistical methods. Results show that:

- *Belarus prefers to import goods over services since the percentage of imports of goods on the total of imports is equal to 88.60% in the period 2012-2018;*
- *Imports in Belarus lack of geographical diversification;*
- *The main part of imports is based on raw material orientation;*
- *Belarus depends on Russia Federation for imports.*

These results suggest that Belarus should diversify its imports on a geographical point of view and at the same time should also promote a deeper economic growth of its economy to improve the percentage of services in total imports.

[4] afford a complex analysis among various instruments that have a real impact on international trade using vector error correction model in the period 1981-2015 in Nigeria. The authors analyze the relationships among the sequent variables:

- *Foreign Direct Investment;*
- *Domestic Investment;*
- *Exports;*
- *Imports;*
- *Labor Force;*
- *Economic Growth*

Results indicate that:

- *There is no relationship among the variables of the model in the long run;*
- *Imports are positively associated with economic growth and domestic investments in the short run;*
- *In the short run there is a positive relationship labor on one side and exports and Foreign Direct Investments on the other side;*
- *In the short run there is a positive relationship between labor and Foreign Direct Investments-FDI.*

The authors suggests that politicians should promote economic reform in Nigeria to improve GDP growth rate.

[5] afford the question of the relationship among exports, imports and economic growth in Panama. The authors analyze data from the period 1980 ed il 2015 using the Johansen co-integration, the Vector Auto Regression Model and the Granger Causality test. Results show that:

- *There is no relationship among exports, imports and economic growth in Panama;*
- *There is a positive relationship between imports and economic growth;*
- *There is a positive relationship between exports and economic growth.*

The authors conclude that there is a positive impact of imports and exports on the economic growth of the economy of Panama.

[6] analyze the relationship between environmental issues and international trade. The authors offer an historical perspective suggesting that the idea of sustainable development has been introduced in the 1992 Rio de Janeiro Summit. The authors analyze the imports of 34 OECD countries in the period 1996-2009.The Environmental Kuznets Curve-EKC is used to quantify the environmental impact of air pollution associated to the imports of environmental goods. Results show that there is a positive relationship between the increasing of imports of environmental goods and the reduction of air pollution.

[7] consider the role of imports and exports on the economic growth of Somalia during the period 1970-1991. The authors use a set of econometric methods such as Ordinary Least Squares-OLS, the Granger Causality, Johansen co-integration tests. Results show that:

- *There is a positive relationship between export and GDP;*
- *There is biunivocal positive relationship between imports and exports;*

The authors conclude that in the case of the economy of Somalia there is a positive relationship between trade, either in the sense of imports either in the sense of exports, and economic growth.

[8] afford the question of the trade relationship between China and India in the period 2002-2016. Specifically the authors apply a model based on the sequent variables:

- *Gdp per capita;*
- *Population;*
- *Per capita gross national product;*
- *Import and export.*

Results show that:

- *Either imports either exports between China and India are increased in the period 2002-2016,*
- *The level of Chinese export towards India is greater then the level of Chinese import to India;*
- *Chinese exports in India are driven by Indian GDP per capita;*
- *Chinese imports to India are associated to Chinese GDP growth.*

[9] afford the question of the relationship between imports and economic growth in Pakistan. The authors use Granger causality and simple regression tests. The authors use data from the period 1975-2014. Results show that:

- *exist a biunivocal relationship between imports and economic growth in Pakistan;*
- *Pakistan imports essentially capital goods such as machinery groups, chemicals, equipment.*

The authors suggest that, in the case of Pakistan, the increase in imports is positively associated to faster economic growth.

[10] analyze the question of the transmission of knowledge through international trade. The authors suggest that there are three ways that can promote the international transmission of knowledge that are:

- *The import of high-technology goods;*
- *The internationalization of R&D business;*
- *Foreign owned patents.*

Results confirm the presence of the international spillovers in the case of the developed countries. But in the case of developing countries the role of import high-technology goods is higher than in the case of developed countries.

[11] analyze the question of the relationship between capital imports and U.S. economic growth. The authors apply a neo-classical approach to identify the relationship between imports of goods and investment-specific productivity. Results show that:

- *The impact of capital goods imports on U.S. output has been equal to 14 percent since 1975;*

- *There is no relationship between capital goods imports and the reduction in equipment investment;*
- *In the absence of imports of goods the U.S. output per hours should have been lower than 18 percent since 1975 in respect to the present level;*
- *Additional tariffs on capital goods have low effect on the imports in equipment investment.*

The authors demonstrate the capital goods import-dependence of the U.S. growth in productivity.
[12] consider the reduction of imports in Spain in the period between 2008-2013. The reduction of Spanish imports has changed the account balance from a deficit to a surplus in the same period. The authors sustain that there are two different motivations that can justify the reduction of the imports in Spain:

- *The reduction of internal prices;*
- *The long term effect of the 2007-2008 financial crisis.*

Results show that the reduction of Spanish imports is a consequence of the compression of GDP growth that has created a fall in income. The analysis show how the level of imports is positively associated to economic growth.
[13] consider the question of the relationship between the declining of employment in U.S. manufacturing and the improvement of imports of cheap products from China and Mexico. Many political commentators have associated the reduction of employment in manufacturing in U.S. to the sequent three elements:

- *North America Free Trade Agreement-NAFTA;*
- *China's admission to the World Trade Organization-WTO;*
- *The improvement of technology in manufacturing.*

To better analyze these propositions the authors have conducted a time series analysis. Results show that:

- *There is a positive relationship between imports from China and Mexico and US employment in manufacturing;*
- *There is a negative relationship between the admission of China to WTO and the US employment in manufacturing.*
- *There is no effect of NAFTA on U.S. employment in manufacturing.*

[14] analyze the question of parallel import in China. The practice of parallel import consists in the imports and selling of goods without the permission of the domestic owner of IP. The author focuses its attention to the parallel import between China and the United States. China and U.S. have different

parallel import policies, but both the countries have subscribed the international IP treaties. While on one side U.S. tends to reject the practice of parallel imports, on the other side China permits parallel imports of goods. But the practice of parallel imports in China is associated to increasing legal costs. The authors propose to reduce the practice of parallel imports in China and to create a deeper convergence between Chinese and U.S. laws on parallel imports.

[15] consider the impact of high-tech imports in Russia. The author used the classification of OECD high technological goods with an adjunction of new goods and a classification of goods based on differentiated levels of technology. A classification of countries based on the degree of high-tech good is proposed. Results show that China, Germany, Republic of Korea, Switzerland, and Singapore are the leading countries in exports of high-tech products through a calculation of net exports. The authors also analyze the Russian competitive index and consider the economic consequences of the imposed sanctions against Russia. The analysis shows that:

- *The Russian economy is dependent on imports of medical and electrical equipment, machinery, and pharmaceutical goods;*
- *The sanctions imposed to Russia have reduced the imports of medical, optical, mechanical equipment and pharmaceutical goods.*

[16] sustain the question of the relationship between political and legal systems of the exporter of meat and the characteristics of the internal market in China as importer of meat. The authors suggest that more stringent institutions in the exporting countries could benefit the importer countries either for judicial questions either for food security. To analyze the relationship between exporting countries and China the authors perform a gravity model for the period 1990-2013. Results show that:

- *Institutions in exporting countries have a role in determining Chinese imports of meat;*
- *Countries that have better qualitative institutions exports more in China;*
- *Countries that are geographically closer to China have greater probabilities to exports meat in China;*
- *The Chinese imports of meat growths with GDP level.*

The authors confirm their hypothesis that there is a positive relationship between the quality of institutions of exporting countries and the degree of meat imports in China-

[17] analyze the impact of imports and exports on economic growth in Tunisia in the period 1977-2012. The authors use the econometric tool of Granger Causality. Results show that:

- *Economic growth is positively associated to imports;*

- *Exports are positively associated to imports.*

The authors conclude that the increasing of imports in Tunisia is the main driver of the economic growth.
[18] analyze the relationship between exports and imports of goods and services in respect to three Indian macro-economic variables i.e.:

- *Exchange rate volatility;*
- *Inflation;*
- *Economic output.*

The authors use AutoRegressive Distributed Lag in the period 2011-2020. Results show that:

- *There is a positive relationship between output growth and trade in goods and services in the long run;*
- *There is a negative relationship between inflation and exports of goods;*
- *There is a negative relationship between volatility and imports of goods in the short run;*
- *There is a positive relationship between volatility and exports of goods in the long run;*
- *There is a positive relationship between inflation and imports of goods in the short run.*

The results suggests that either volatility either inflation have a positive impact on imports of goods in the short run.
[19] scrutinize the existence of a positive relationship between imports and economic growth in Turkey in the period 1960-2017. Annual data are analyzed with a Times Series approach through the application of Autoregressive Distributed Lag-ARDL. The analysis is oriented to investigate the relationship between imports and economic growth either in the short term either in the long term. The authors also check the relationship through the application of Granger causality. Results show that:

- *There is a positive relationship between imports and economic growth either in the short term either in the long term in Turkey;*
- *Economic growth Granger causes imports;*
- *The confirmation of a Granger causation between imports and economic growth is absent.*

In the case of Turkey, the increase in GDP augments imports.

3. The model

We estimated the sequent model:

$$\begin{aligned} \boldsymbol{ImportsOfGoods_{it}} &= \boldsymbol{a_1 + b_1(PrivateConsumptionExpenditure)_{it}} \\ &\quad \boldsymbol{+ b_2(ConsumerPriceIndex)_{it} + b_3(ConsumptionOfFixedCapital)_{it}} \\ &\quad \boldsymbol{+ b_4(GrossDomesticProduct)_{it} + b_5(OperatingSurplusTotalEconomy)_{it}} \end{aligned}$$

We use data from AMECO, a dataset from Eurostat [18], and use Panel Data With Fixed Effects, Panel Data With Random Effects, Pooled OLS, and WLS. We found that the level of imports of goods is positively associated to:

- *Consumer Price Index:* the level of consumer price index is a proxy of inflation. The increasing of inflation is positively associated to an increase in imports of goods. The positive impact of inflation on import of goods can be effectively since consumers in countries with higher inflation are oriented to pay a good more than in a country with lower inflation.
- *Operating Surplus Total Economy:* is a proxy for total pre-tax profit income. There is a positive relationship between the total pre-tax and imports of goods. This positive relationship can be explained because many imports are input factors in the firm productivity function. If firms increase their income, then they can improve the imports of goods as inputs.

We also found that the level of "*Imports of Goods*" is negatively associated to:

- *Private Final Consumption Expenditure:* is a measure of expenditures on goods and services of families and individuals. The increase in expenditure of goods and services is negatively associated to imports of goods. This negative relationship can be better understood considering that the main part of imports is input for firm's productivity function. Countries that are analyzed in the dataset are not importers of goods for the consumption of individuals and families.
- *Consumption of Fixed Capital:* is the reduction of value of fixed assets of enterprises, government, and owners of dwellings. The reduction of "*Consumption of Fixed Capital*" is negatively associated to the "*Imports of Goods*". Since, as showed in the results, "*Imports of Goods*" are associated to input of firms' production function, the reduction of "*Consumption of Fixed Capital*" shows the absence of investment in long term asset that are generally imported in the economies of analyzed countries.
- *Gross Domestic Product:* is the sum of all incomes in a country. There is a negative relationship between the increasing of "*Gross Domestic Product*" and the "*Imports of Goods*". This negative relationship can seem counterfactual since the economic literature sustains that there is a positive

relationship between "*Gross Domestic Product*" and imports. The main explanation can be found considering that the dependent variable i.e., "*Imports of Goods*" does not consider the imports of services. Generally high-income and middle-income countries imports more services than goods since the imports of goods are essentially imports of inputs for the manufacturing sector. High- and middle-income countries tend to have lower levels of manufacture in respect to low-income countries and, therefore, also have lower levels of "*Imports of Goods*".

Variable		Description	Label	Relations	Models
y	*Imports of Goods*	Imports of goods at current prices (National accounts)	A381		
x_1	*Private Final Consumption Expenditure*	Private final consumption expenditure at current prices	A27	Negative	Pooled OLS, Fixed Effects, Random Effects, WLS.
x_2	*Consumer Price Index*	Harmonised consumer price index (All-items)	A48	Positive	Pooled OLS, Fixed Effects, Random Effects, WLS.
x_3	*Consumption of Fixed Capital*	Total economy	A92	Negative	Pooled OLS, Fixed Effects, Random Effects, WLS.
x_4	*Gross Domestic Product*	Gross domestic product at current prices	A214	Negative	Pooled OLS, Fixed Effects, Random Effects, WLS.
x_5	*Operating Surplus, Total Economy*	Gross operating surplus: total economy	A301	Positive	Pooled OLS, Fixed Effects, Random Effects, WLS.

4. The predictive model

We have also realized a predictive model using RapidMiner. We use the dependent variables of the model i.e. "*Private Consumption Expenditure",* "*Consumer Price Index*", "*Consumption of Fixed Capital*", "*Gross Domestic Products*", "*Operating Surplus of Total Economy*" to predict the independent variables i.e. "*Imports of Goods*". We found that in order Random Forest, Gradient Boosted Trees, and Decision Tree are more efficient in respect to Deep Learning, Generalized Linear Model and Support Vector Machine, in the sense of error minimization, to forecast the degree of "*Imports of Goods*". Specifically, we analyze different typologies of errors that are: "*Root Mean Squared Error*", "*Squared Errors*", "*Relative Errors*", "*Absolute Errors*". We confront different machine learning techniques and order them summing up the rank in each of the charts as showed in the following figure.

Synthesis of the Main Results of the Prediction Model. Source: Eurostat						
Rank	Model	Root Mean Squared Error	Standard Deviation	Total Time	Training Time (1,000 Rows)	Scoring Time (1,000 Rows)
1	*Random Forest*	922497,435339875	90026,656160	4465,0	537,037037037037	472,2222222222220
2	*Gradient Boosted Trees*	971060,312703302	236437,603188	31992,0	1344,44444444440	64,8148148148148
3	*Decision Tree*	1212269,318826020	324587,707440	393,0	22,222222222222	55,5555555555556
4	*Deep Learning*	1600305,371486900	162458,030672	1710,0	1492,59259259259	101,8518518518520
5	*Generalized Linear Model*	1683242,130542020	106533,481647	2344,0	1281,481481481480	166,6666666666670
6	*Support Vector Machine*	2139021,568286280	263114,394067	1219,0	107,407407407407	46,2962962962963
Rank	Model	Correlation	Standard Deviation	Total Time	Training Time (1,000 Rows)	Scoring Time (1,000 Rows)
1	*Support Vector Machine*	0,5694936232367480	0,17997754536	1219,0	107,407407407407	46,296296296296
2	*Generalized Linear Model*	0,5852680388210990	0,19031420816	2344,0	1281,481481481480	166,666666666667
3	*Deep Learning*	0,6162827307763340	0,19015096597	1710,0	1492,59259259259	101,851851851852
4	*Decision Tree*	0,7923807677379740	0,09991263361	393,0	22,222222222222	55,555555555556
5	*Gradient Boosted Trees*	0,8497561346796910	0,09909849722	31992,0	1344,44444444440	64,814814814815
6	*Random Forest*	0,9164668183026170	0,04828851473	4465,0	537,037037037037	472,222222222222
Rank	Model	Squared Error	Standard Deviation	Total Time	Training Time (1,000 Rows)	Scoring Time (1,000 Rows)
1	*Random Forest*	857485357264,18500	166128706768,7	4465,0	537,037037037	472,2222222222220
2	*Gradient Boosted Trees*	987680323068,39700	449943781230,9	31992,0	1344,444444444	64,8148148148148
3	*Decision Tree*	1553882645223,65000	829944501485,7	393,0	22,222222222	55,5555555555556
4	*Deep Learning*	2582091371393,65000	511810865757,9	1710,0	1492,592592593	101,8518518518520
5	*Generalized Linear Model*	2842383576201,18000	369517538067,8	2344,0	1281,481481481	166,6666666666670
6	*Support Vector Machine*	4630796617086,25000	1144584118919,9	1219,0	107,407407407	46,2962962962963
Rank	Model	Relative Error	Standard Deviation	Total Time	Training Time (1,000 Rows)	Scoring Time (1,000 Rows)
1	*Decision Tree*	0,1776950109520110	0,01897387854	393,0	22,2222222222	55,555555555556
2	*Gradient Boosted Trees*	0,2165174711166850	0,02802951768	31992,0	1344,4444444444	64,814814814815
3	*Random Forest*	0,2608696716136780	0,04919070198	4465,0	537,0370370370	472,222222222222
4	*Deep Learning*	0,3931418489501480	0,04010481921	1710,0	1492,5925925926	101,851851851852
5	*Generalized Linear Model*	0,3957876220780940	0,02213534737	2344,0	1281,4814814815	166,666666666667
6	*Support Vector Machine*	0,4498833193122640	0,02878264392	1219,0	107,4074074074	46,296296296296
Rank	Model	Absolute Error	Standard Deviation	Total Time	Training Time (1,000 Rows)	Scoring Time (1,000 Rows)
1	*Gradient Boosted Trees*	601070,57512497800	49935,128751737	31992,0	1344,44444444440	64,81481481481480
2	*Decision Tree*	621696,71432600700	119526,994101566	393,0	22,222222222222	55,55555555555560
3	*Random Forest*	732090,93610286600	57400,444054832	4465,0	537,037037037037	472,22222222222200
4	*Deep Learning*	1301049,69873069000	52565,935057314	1710,0	1492,59259259259	101,85185185185200
5	*Generalized Linear Model*	1376814,16534176000	99443,137693513	2344,0	1281,481481481480	166,66666666666700
6	*Support Vector Machine*	1851655,38743900000	169757,782497067	1219,0	107,407407407407	46,29629629629630

Figure 1. Synthesis of the main results of the predictive model with RapidMiner. Source: Eurostat.

Finally, we create a new chart of the different machine learning techniques based on the minimum rank and we found the sequent order:

1. *Gradient Boosted Trees*: is a machine learning technique that generates a prediction model based on decision trees. Generally, a "*Gradient Boosted Tree*" outperforms the "*Random Forest*". In our simulation of a predictive model to estimate the degree of "*Imports of Goods*" based on the proposed econometric model, we found that the "*Gradient Boosted Trees*" has the best payoffs of 7 based on the sum of the different ranking in the charts of error minimization.
2. *Random Forest*: is a machine learning method that is based on multiple decision tree at a training time. "*Random Forests*" are more efficient than "*Decision Trees*" since "*Random Forests*" corrects for the overfitting of the training set. In our predictive model "Random Forest" has the

second rank in the sense of the cumulative efficacy in the minimization of different set of errors with a payoff equal to 8.

3. *Decision Tree*: is a methodology for decision support that simulate the model of a tree. "*Decision Tree*" defines an algorithm that is conditioned based on normative rules. In our application we use "*Decision Tree*" as a machine learning technique to predict the degree of "*Imports of Goods*" with the variables indicated in the estimated econometric equation. "*Decision Tree*" is the third methodology for the efficiency of prediction in the sense of minimization of errors with a payoff equal to 9.

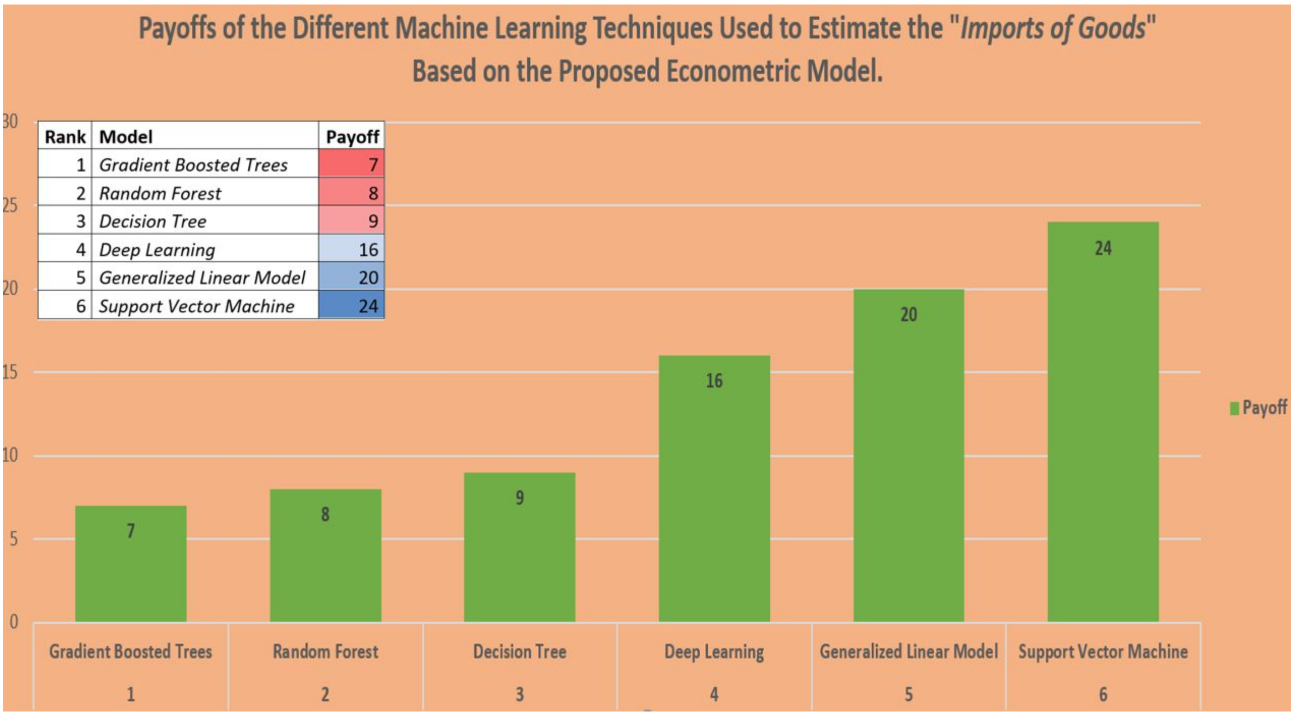

Figure 2. Ranking of machine learning techniques used to predict the degree of "Imports of Goods" based on the variables of the estimated econometric model.

4. *Deep Learning*: is a methodology to perform machine learning based on artificial neural networks. In our case we use "*Deep Learning*" to predict the degree of "*Imports of Goods*". We found that summing up the rank in the charts of minimization of errors, "*Deep Learning*" is at the fourth rank with a payoff equal to 16.

5. *Generalized Linear Model*: is a generalization of linear regression. In our predictive model, oriented to estimate the degree of "*Imports of Goods*", the Generalized Linear Model is at the fifth rank in the sense of minimization of multiple errors with a payoff equal to 20.

6. *Support Vector Machine*: is an algorithm-based machine learning technique to investigate meaning in data. We use the "*Support Vector Machine*" to predict the level of "*Imports of Goods*"

based on the variables of the econometric model. We found that the "*Support Vector Machine*" is the last model for the predictive efficacy in the sense of error minimization with a total payoff equal to 24.

Our analysis with RapidMiner show that using the variables of the econometric model estimated in the third paragraph it is possible to predict the degree of "*Imports of Goods*" and that "*Gradient Boosted Trees*" is the best algorithm to perform the prediction.

7. Conclusion

In this article we have estimated the "*Imports of Goods*" in 28 European countries in the period 2010-2019. We present a brief synthesis of the main international trade theory showing that, as indicated in the new trade theory, the level of imports can work as a driver for the implementation of political economy oriented to industrial localization. In effect firms that export can have an economic convenience in locating their plants in countries with sustained domestic demand to reduce transportation costs and improve the level of increasing return of scales. In the second paragraph we present an analysis of the economic literature on the macro-economic role of the imports of goods. In the third paragraph we estimate an econometric model using Panel Data with Fixed Effects, Panel Data with Random Effects, Pooled OLS, WLS. Our results show that "*Imports of Goods*" is negatively associated with "*Private Consumption Expenditure at Current Prices*", "*Consumption of Fixed Capital*", and "*Gross Domestic Product*" and positively associated with "*Harmonised consumer price index*" and "*Gross Operating Surplus: Total Economy*". Our results show that there are significant differences among medium and high-level income and low income in the sense of imports of goods. In effect while, on one side, the imports of goods are positively associated to GDP in low-income countries, as showed in the second paragraph, on the other side the imports of goods are negatively associated to GDP in medium and high-income countries, as showed in the econometric estimation in the third paragraph. This can be since middle- and high-income countries tend to import more services rather than goods. Furthermore, "*Imports of Goods*" is positively associated to "*Gross Operating Surplus*" suggesting that the 28 European countries analyzed tend to import factor of production for their firms. This fact, according to the new trade theory, could lead to political economies oriented to promote the localization of foreign firms near the domestic market to reduce the transportation costs and develop a deeper control overo domestic demand. Finally, in the fourth paragraph we apply a set of predictive models based on different machine learning techniques using RapidMiner, and we find that “*Gradient Boosted Trees*”, “*Random Forest*”, and “*Decision Tree*” are more efficient then “*Deep Learning*”, “*Generalized Linear Model*” and “*Support Vector Machine*”, in the sense of error minimization, to forecast the degree of “*Imports of Goods*”.

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9. Appendix

Model 54: Pooled OLS, using 270 observations					
Including 27 cross section units					
Time series length = 10					
Dependent variable: A381					
	Coefficient	*Std. Error*	*t*	*p-value*	
const	−5,93350e+06	2,64577e+06	−2,243	0,0258	**
A27	−0,155547	0,0708341	−2,196	0,0290	**
A48	0,0100635	0,00275124	3,658	0,0003	***
A92	−0,199587	0,0537260	−3,715	0,0002	***
A214	−0,241931	0,0318642	−7,593	<0,0001	***
A301	0,281690	0,0424361	6,638	<0,0001	***

Average var. employee	3183319	Dependent variable root mean square	2051878
Quadratic sum of residuals	6,98e+14	Standard error of the regression	1626551
R-square	0,383286	Correct R-square	0,371606
F (5, 264)	32,81501	P-value (F)	5,47e-26
Log-likelihood	−4241,612	Akaike's criterion	8495,224
Schwarz's criterion	8516,815	Hannan-Quinn	8503,894

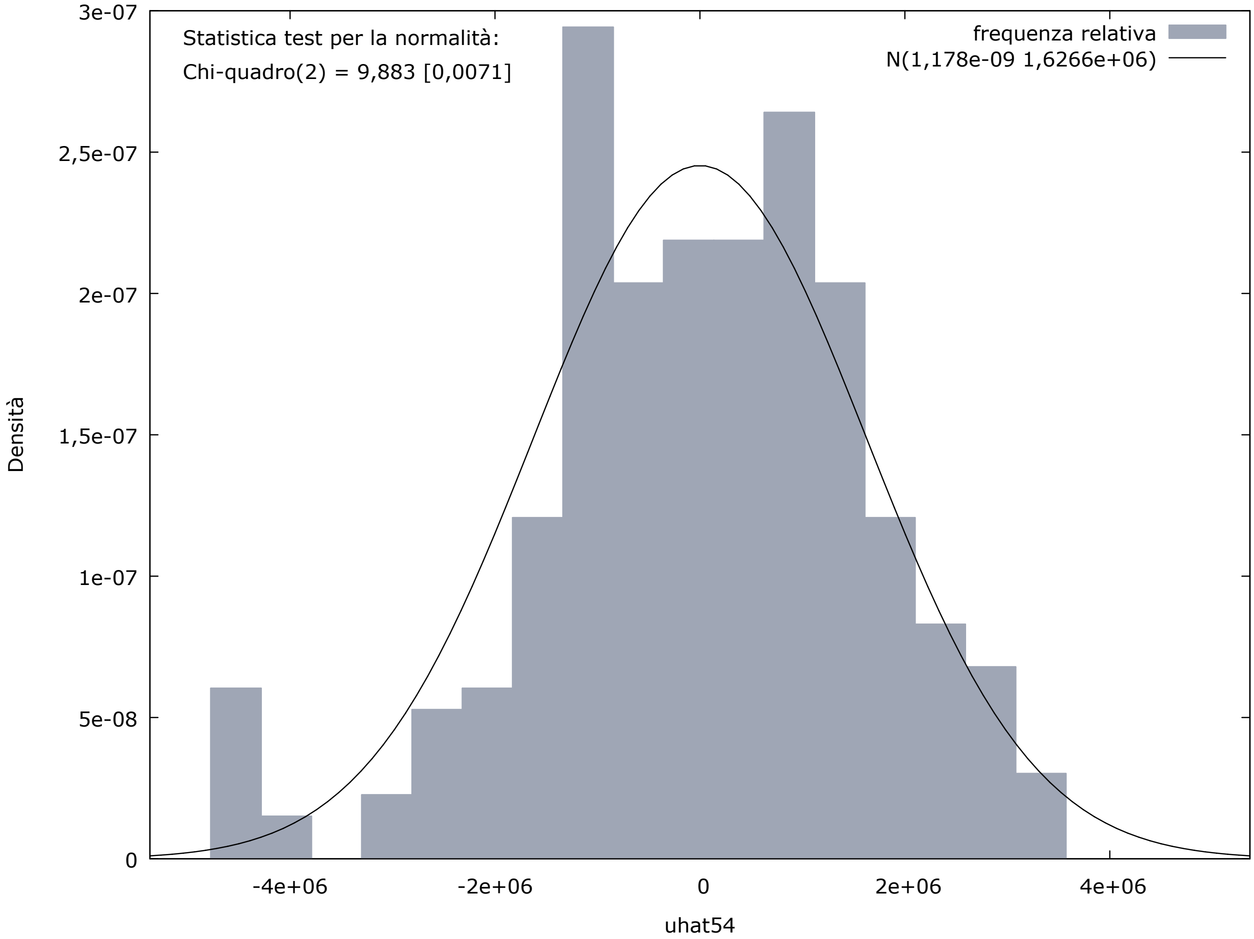
```
Regressione ausiliaria con l'aggiunta dei residui ritardati:

             coefficiente    errore std.     rapporto t   p-value
  -----------------------------------------------------------
  const      -6,34744e+06  494474             -12,84    9,28e-013 ***
  A27        -0,136208          0,0114937     -11,85    5,53e-012 ***
  A48         0,0103732         0,000505948    20,50    1,42e-017 ***
  A92        -0,201328          0,00492242    -40,90    3,95e-025 ***
  A214       -0,229086          0,00248026    -92,36    2,92e-034 ***
  A301        0,292328          0,00417994     69,94    3,93e-031 ***
  uhat(-1)    1,01178           0,00859814    117,7     5,46e-037 ***

  n = 243, R-squared = 0,9874

Test di Wooldridge per l'autocorrelazione in dati panel -
  Ipotesi nulla: Non c'è utocorrelazione del prim'ordine (rho = 0)
  Statistica test: t(26) = 117,675
  con p-value = P(|t| > 117,675) = 5,45709e-037
Diagnostiche: incluse n = 27 unità longitudinali

Stimatore a effetti fissi
implica intercette diverse per ogni unità longitudinale
```

```
             coefficiente    errore std.     rapporto t   p-value
  -------------------------------------------------------------
  const     -2,67852e+06  600587              -4,460    1,26e-05  ***
  A27         0,284993       0,0872565         3,266    0,0013    ***
  A48         0,00481235     0,000810832       5,935    1,03e-08  ***
  A92        -0,259107       0,0720334        -3,597    0,0004    ***
  A214       -0,0576653      0,0261581        -2,204    0,0284    **
  A301        0,484934       0,0717562         6,758    1,07e-010 ***

Varianza dei residui: 1,9539e+013/(270 - 32) = 8,20965e+010

Significatività congiunta delle differenti medie dei gruppi:
 F(26, 238) = 318,067 con p-value 3,30749e-169
(un basso p-value conta contro l'ipotesi nulla che il modello pooled OLS
sia adeguato, in favore del modello alternativo con effetti fissi)

Variance estimators:
 between = 3,12018e+012
 within = 8,20965e+010
theta used for quasi-demeaning = 0,948773
```

```
Stimatore a effetti casuali
comprende una componente specifica per ogni unità del termine di errore

             coefficiente    errore std.     rapporto t   p-value
  -------------------------------------------------------------
  const     -2,59813e+06  685313              -3,791    0,0002    ***
  A27         0,255914       0,0796118         3,215    0,0015    ***
  A48         0,00467236     0,000792816       5,893    1,15e-08  ***
  A92        -0,205419       0,0657355        -3,125    0,0020    ***
  A214       -0,0648101      0,0250522        -2,587    0,0102    **
  A301        0,470037       0,0630285         7,458    1,27e-012 ***


Statistica test di Breusch-Pagan:
 LM = 1087,83 con p-value = prob(chi-quadro(1) > 1087,83) = 1,45953e-238
(un basso p-value conta contro l'ipotesi nulla che il modello pooled OLS
sia adeguato, in favore del modello alternativo con effetti casuali)

Statistica test di Hausman:
 H = 9,35444 con p-value = prob(chi-quadro(5) > 9,35444) = 0,0957349
(un basso p-value conta contro l'ipotesi nulla che il modello con coefficienti
casuali sia adeguato, in favore del modello con effetti fissi)
```

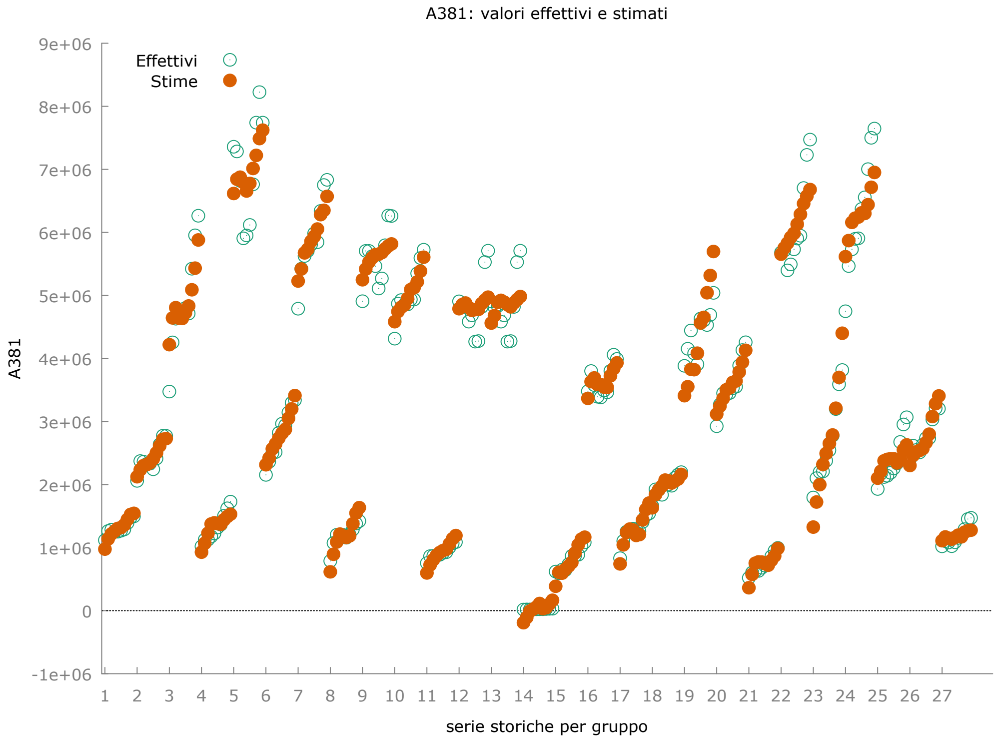
```
Fattori di Inflazione della Varianza (VIF)
Valore minimo possibile = 1.0
Valori oltre 10.0 indicano un problema di collinearità

         A27    1,332
         A48    1,124
         A92    1,417
        A214    1,170
        A301    1,176

VIF(j) = 1/(1 - R(j)^2), dove R(j) è il coefficiente di correlazione multipla
tra la variabile j e le altre variabili indipendenti
```

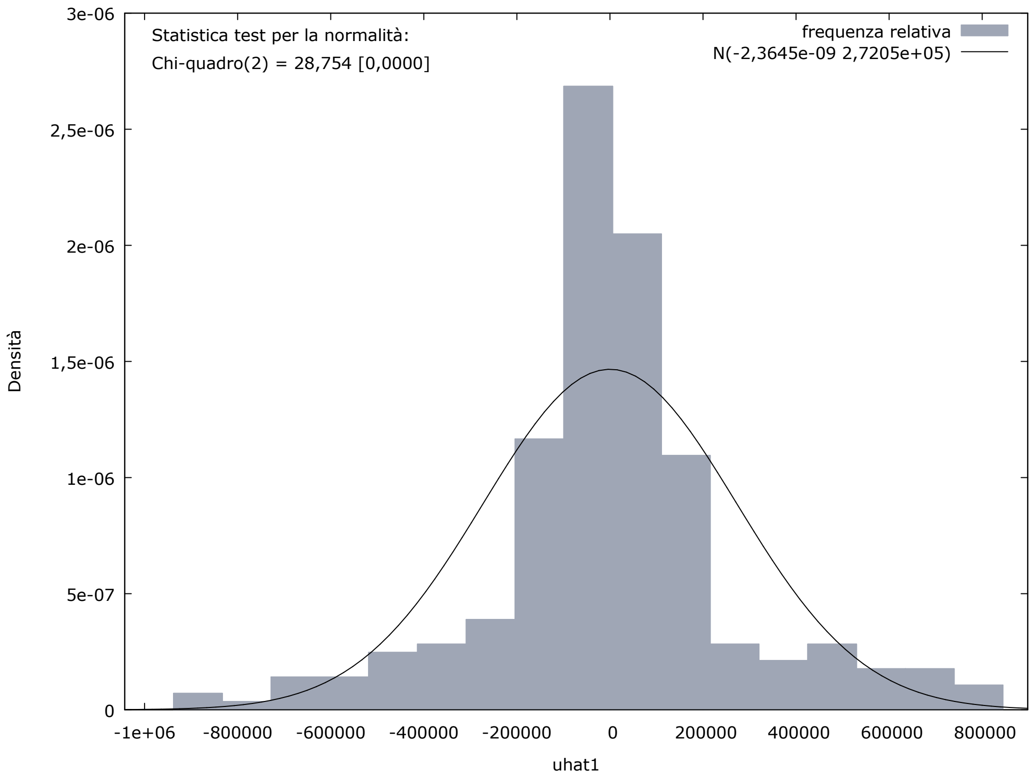
```
Diagnostiche di collinearità di Besley, Kuh e Welsch:

  proporzioni della varianza

  lambda     cond   const     A27     A48     A92    A214    A301
   4,577    1,000   0,000   0,009   0,000   0,007   0,011   0,011
   0,635    2,684   0,000   0,070   0,000   0,012   0,409   0,113
   0,418    3,311   0,000   0,067   0,000   0,253   0,290   0,041
   0,299    3,915   0,000   0,400   0,000   0,000   0,011   0,585
   0,070    8,080   0,006   0,414   0,005   0,673   0,260   0,241
   0,001   82,252   0,994   0,040   0,995   0,056   0,019   0,009

  lambda = Autovalori dell'inversa della matrice di covarianza (smallest is 0,000676605)
  cond   = indice di condizione
  nota: le colonne delle proporzioni di varianza sommano ad uno

Secondo BKW, cond >= 30 indica quasi-dipendenza lineare "forte"
e cond fra 10 e 30 "moderatamente forte".  Stime dei parametri
la cui varianza
è associata a valori di cond problematici potrebbero essere
a loro volta problematiche.

Numero dei condtion index >= 30: 1
Proporzioni di varianza >= 0.5 associate a cond >= 30:

   const     A48
   0,994   0,995

Numero dei condtion index >= 10: 1
```



Modello 1: Effetti fissi, usando 270 osservazioni					
Incluse 27 unità cross section					
Lunghezza serie storiche = 10					
Variabile dipendente: A381					
	Coefficiente	*Errore Std.*	*rapporto t*	*p-value*	
const	−2,67852e+06	600587	−4,460	<0,0001	***
A27	0,284993	0,0872565	3,266	0,0013	***
A48	0,00481235	0,000810832	5,935	<0,0001	***
A92	−0,259107	0,0720334	−3,597	0,0004	***
A214	−0,0576653	0,0261581	−2,204	0,0284	**
A301	0,484934	0,0717562	6,758	<0,0001	***
Media var. dipendente	3183319	SQM var. dipendente	2051878		

Somma quadr. residui	1,95e+13	E.S. della regressione	286524,9
R-quadro LSDV	0,982748	R-quadro intra-gruppi	0,598545
LSDV F(31, 238)	437,3319	P-value(F)	1,1e-191
Log-verosimiglianza	−3758,790	Criterio di Akaike	7581,579
Criterio di Schwarz	7696,729	Hannan-Quinn	7627,819
rho	0,700977	Durbin-Watson	0,514522
Test congiunto sui regressori -			
Statistica test: F(5, 238) = 70,9688			
con p-value = P(F(5, 238) > 70,9688) = 3,15159e-045			
Test per la differenza delle intercette di gruppo -			
Ipotesi nulla: i gruppi hanno un'intercetta comune			
Statistica test: F(26, 238) = 318,067			
con p-value = P(F(26, 238) > 318,067) = 3,30749e-169			





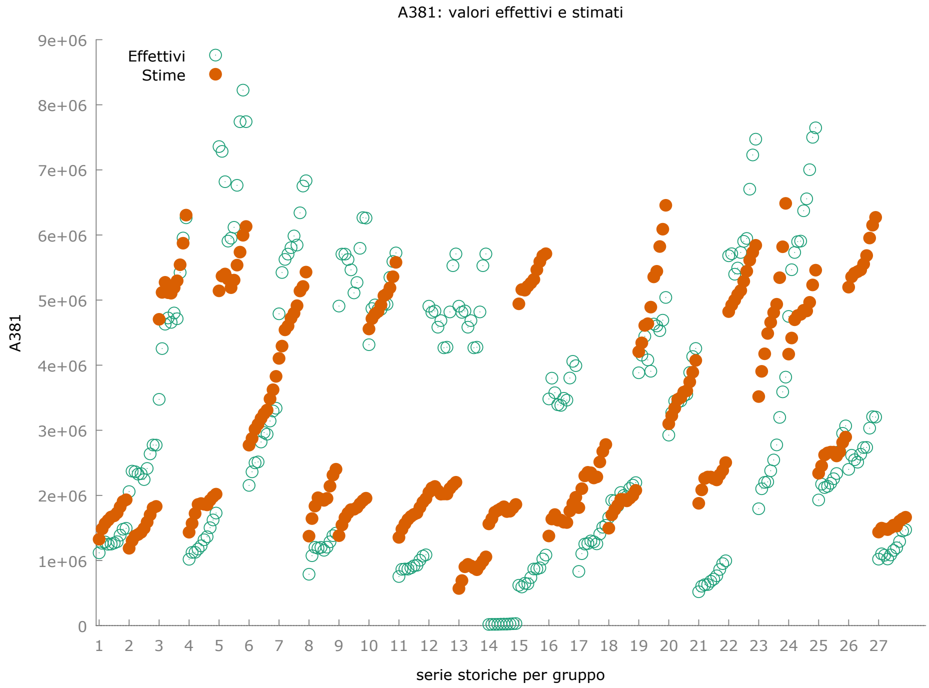
Distribuzione di frequenza per uhat1, oss. 1-270					
Numero di intervalli = 17, media = -2,36452e-009, scarto quadratico medio = 272050					
Intervallo	P.med.	Frequenza	Rel.	Cum.	
< -8,330e+005	-8,854e+005	2	0,74%	0,74%	
-8,330e+005 - -7,282e+005	-7,806e+005	1	0,37%	1,11%	
-7,282e+005 - -6,233e+005	-6,757e+005	4	1,48%	2,59%	
-6,233e+005 - -5,185e+005	-5,709e+005	4	1,48%	4,07%	
-5,185e+005 - -4,136e+005	-4,661e+005	7	2,59%	6,67%	
-4,136e+005 - -3,088e+005	-3,612e+005	8	2,96%	9,63%	*
-3,088e+005 - -2,040e+005	-2,564e+005	11	4,07%	13,70%	*
-2,040e+005 - -9,912e+004	-1,515e+005	33	12,22%	25,93%	****
-9,912e+004 - 5724,	-4,670e+004	76	28,15%	54,07%	**********
5724, - 1,106e+005	5,814e+004	58	21,48%	75,56%	*******
1,106e+005 - 2,154e+005	1,630e+005	31	11,48%	87,04%	****
2,154e+005 - 3,202e+005	2,678e+005	8	2,96%	90,00%	*
3,202e+005 - 4,251e+005	3,727e+005	6	2,22%	92,22%	
4,251e+005 - 5,299e+005	4,775e+005	8	2,96%	95,19%	*
5,299e+005 - 6,348e+005	5,824e+005	5	1,85%	97,04%	
6,348e+005 - 7,396e+005	6,872e+005	5	1,85%	98,89%	
>= 7,396e+005	7,920e+005	3	1,11%	100,00%	
Test per l'ipotesi nulla di distribuzione normale:					
Chi-quadro(2) = 28,754 con p-value 0,00000					

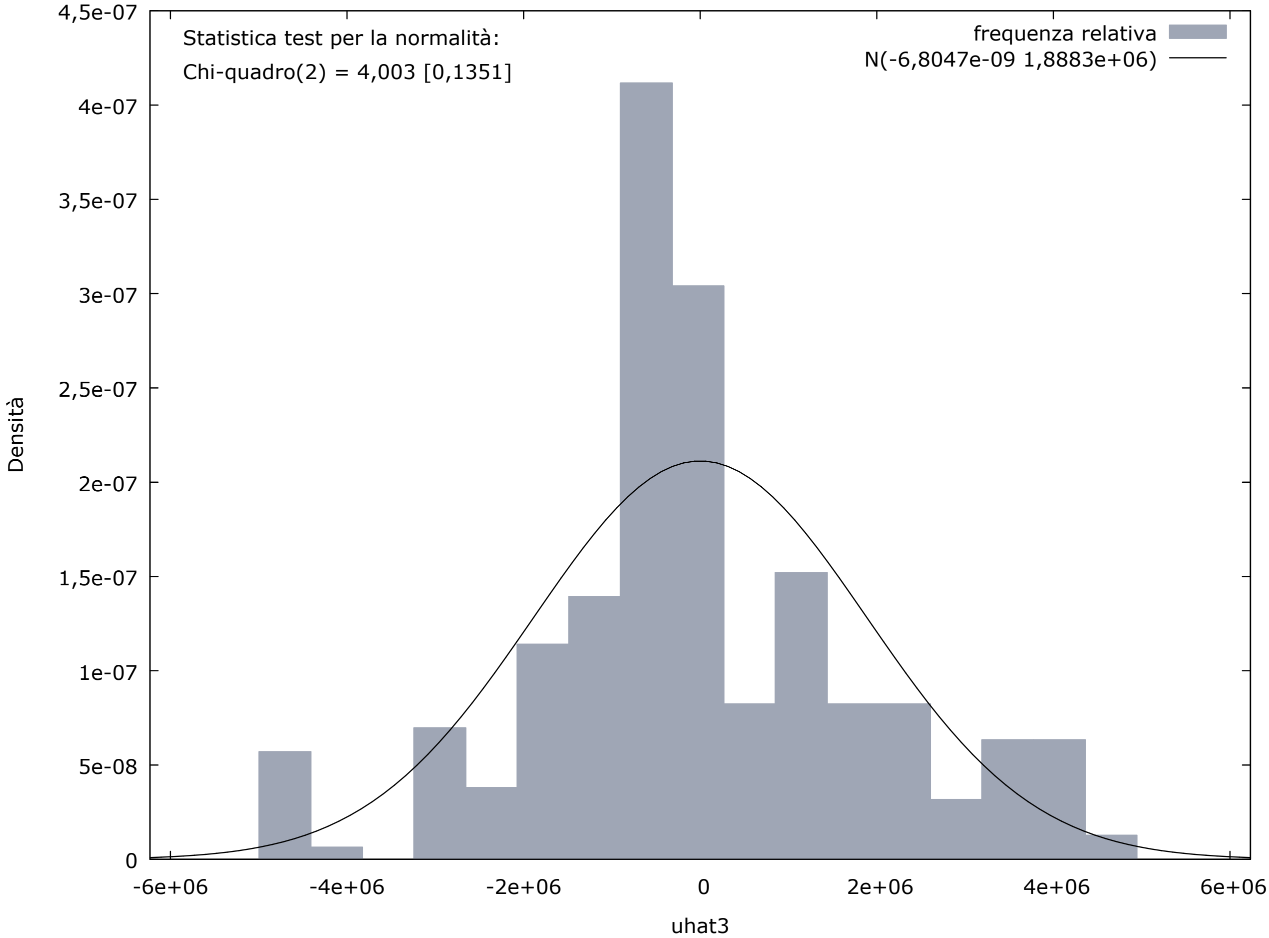
Modello 5: Effetti casuali (GLS), usando 270 osservazioni

Con trasformazione di Nerlove					
Incluse 27 unità cross section					
Lunghezza serie storiche = 10					
Variabile dipendente: A381					
	Coefficiente	*Errore Std.*	*z*	*p-value*	
const	−2,61240e+06	707409	−3,693	0,0002	***
A27	0,262950	0,0803218	3,274	0,0011	***
A48	0,00469731	0,000786871	5,970	<0,0001	***
A92	−0,217213	0,0663565	−3,273	0,0011	***
A214	−0,0630516	0,0249913	−2,523	0,0116	**
A301	0,473428	0,0641719	7,378	<0,0001	***

Media var. dipendente	3183319	SQM var. dipendente	2051878
Somma quadr. residui	9,41e+14	E.S. della regressione	1884766
Log-verosimiglianza	−4281,905	Criterio di Akaike	8575,810
Criterio di Schwarz	8597,400	Hannan-Quinn	8584,479
rho	0,700977	Durbin-Watson	0,514522

Varianza 'between' = 3,74714e+012
Varianza 'within' = 7,23665e+010
Theta usato per la trasformazione = 0,956096
Test congiunto sui regressori -
Statistica test asintotica: Chi-quadro(5) = 363,294
con p-value = 2,40172e-076
Test Breusch-Pagan -
Ipotesi nulla: varianza dell'errore specifico all'unità = 0
Statistica test asintotica: Chi-quadro(1) = 1087,83
con p-value = 1,45953e-238
Test di Hausman -
Ipotesi nulla: le stime GLS sono consistenti
Statistica test asintotica: Chi-quadro(5) = 7,23073
con p-value = 0,204038


A381: valori effettivi e stimati
Effettivi
Stime
A381
9e+06
8e+06
7e+06
6e+06
5e+06
4e+06
3e+06
2e+06
1e+06
0
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27
serie storiche per gruppo



Diagnostiche di collinearità di Besley, Kuh e Welsch:

proporzioni della varianza

lambda	cond	const	A27	A48	A92	A214	A301
3,437	1,000	0,011	0,019	0,010	0,019	0,020	0,021
0,991	1,863	0,156	0,029	0,018	0,000	0,146	0,042
0,747	2,145	0,006	0,146	0,000	0,010	0,576	0,044
0,499	2,623	0,094	0,005	0,004	0,445	0,118	0,087
0,233	3,838	0,000	0,679	0,005	0,043	0,139	0,804
0,093	6,064	0,733	0,122	0,963	0,482	0,001	0,002

lambda = Autovalori dell'inversa della matrice di covarianza (smallest is 0,0934684)
cond   = indice di condizione
nota: le colonne delle proporzioni di varianza sommano ad uno

Secondo BKW, cond >= 30 indica quasi-dipendenza lineare "forte"
e cond fra 10 e 30 "moderatamente forte". Stime dei parametri
la cui varianza
è associata a valori di cond problematici potrebbero essere
a loro volta problematiche.

Numero dei condtion index >= 30: 0

```
Numero dei condtion index >= 10: 0

No evidence of excessive collinearity
```

```
Prima equazione in differenze (dipendente, d_y):

             coefficiente   errore std.   rapporto t   p-value
  ------------------------------------------------------------
  d_A27        0,343887      0,134657         2,554     0,0169  **
  d_A48        0,00459451    0,00109370       4,201     0,0003  ***
  d_A92       -0,294263      0,130323        -2,258     0,0326  **
  d_A214      -0,0427822     0,0380446       -1,125     0,2711
  d_A301       0,486026      0,157961         3,077     0,0049  ***

  n = 243, R-squared = 0,3718

Autoregressione dei residui (dipendente, uhat):

             coefficiente   errore std.   rapporto t   p-value
  -------------------------------------------------------------
  uhat(-1)     0,280888      0,0452520      6,207      1,45e-06 ***

  n = 216, R-squared = 0,0845

Test di Wooldridge per l'autocorrelazione in dati panel -
  Ipotesi nulla: Non c'è autocorrelazione del prim'ordine (rho = -0.5)
  Statistica test: F(1, 26) = 297,785
  con p-value = P(F(1, 26) > 297,785) = 9,2989e-016
```

Modello 4: WLS, usando 270 osservazioni
Incluse 27 unità cross section
Variabile dipendente: A381
Pesi basati sulle varianze degli errori per unità

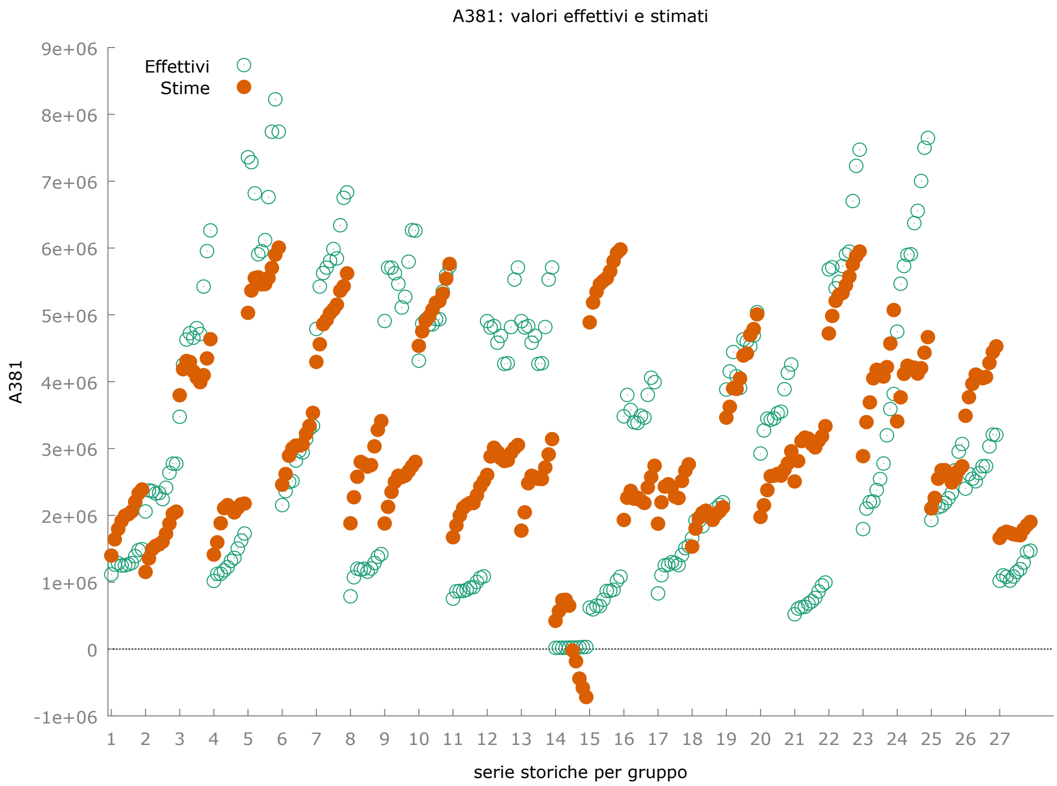
	Coefficiente	*Errore Std.*	*rapporto t*	*p-value*	
const	−5,25720e+06	802465	−6,551	<0,0001	***
A27	−0,129147	0,0337818	−3,823	0,0002	***
A48	0,00886943	0,000912035	9,725	<0,0001	***
A92	−0,190721	0,0156461	−12,19	<0,0001	***
A214	−0,213122	0,0154253	−13,82	<0,0001	***
A301	0,380176	0,0180841	21,02	<0,0001	***

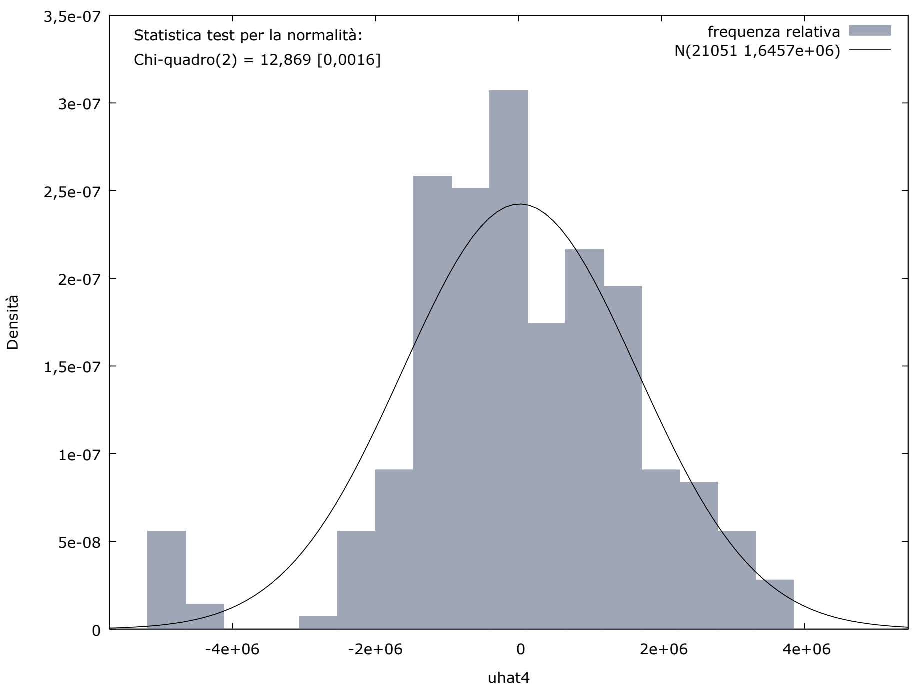
Statistiche basate sui dati ponderati:

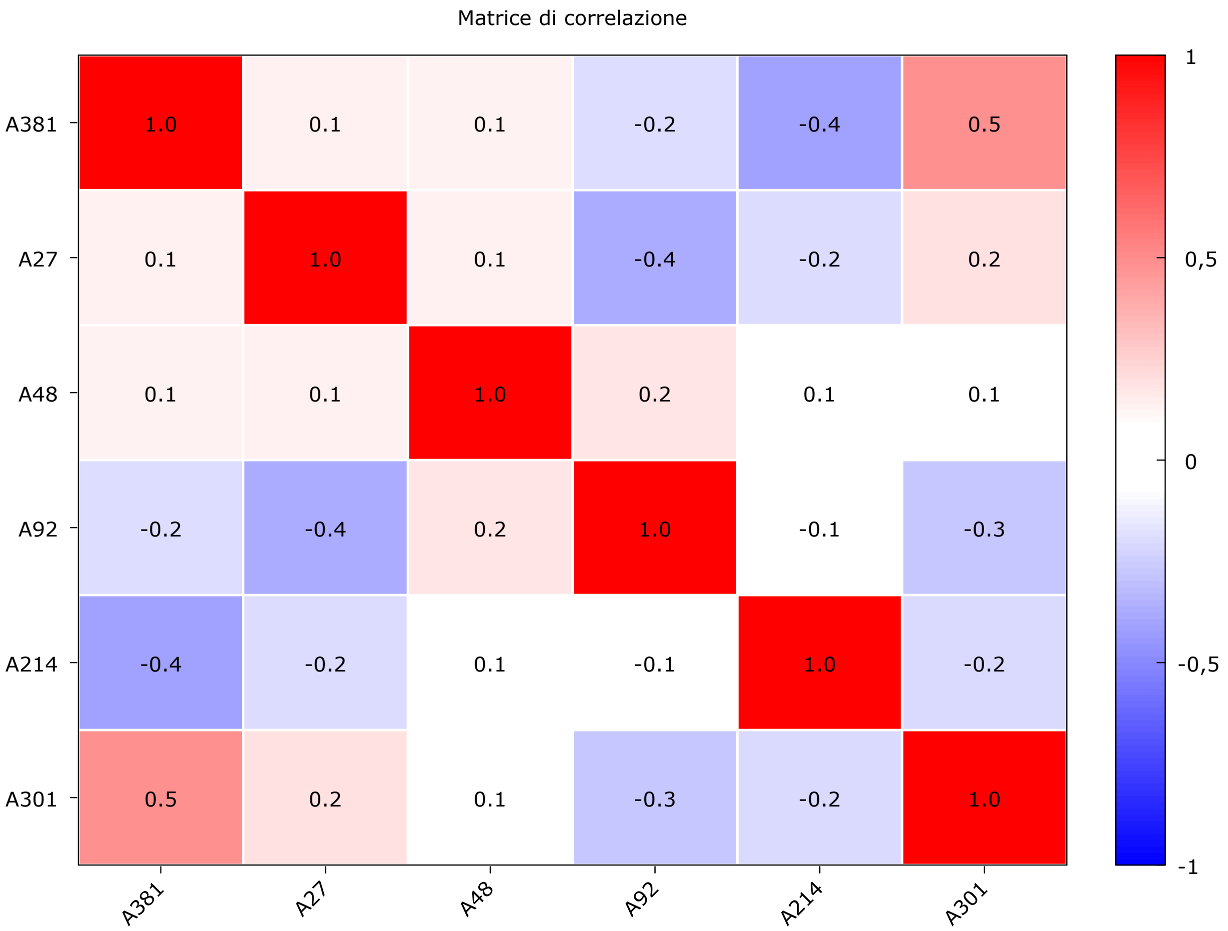
Somma quadr. residui	240,3749	E.S. della regressione	0,954207
R-quadro	0,874164	R-quadro corretto	0,871781
F(5, 264)	366,7931	P-value(F)	1,4e-116
Log-verosimiglianza	−367,4234	Criterio di Akaike	746,8468
Criterio di Schwarz	768,4374	Hannan-Quinn	755,5166

Statistiche basate sui dati originali:

Media var. dipendente	3183319	SQM var. dipendente	2051878
Somma quadr. residui	7,15e+14	E.S. della regressione	1645866


A381: valori effettivi e stimati
Effettivi
Stime
A381
9e+06
8e+06
7e+06
6e+06
5e+06
4e+06
3e+06
2e+06
1e+06
0
-1e+06
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27
serie storiche per gruppo


Statistica test per la normalità:
Chi-quadro(2) = 12,869 [0,0016]
frequenza relativa
N(21051 1,6457e+06)
Densità
3,5e-07
3e-07
2,5e-07
2e-07
1,5e-07
1e-07
5e-08
0
-4e+06
-2e+06
0
2e+06
4e+06
uhat4

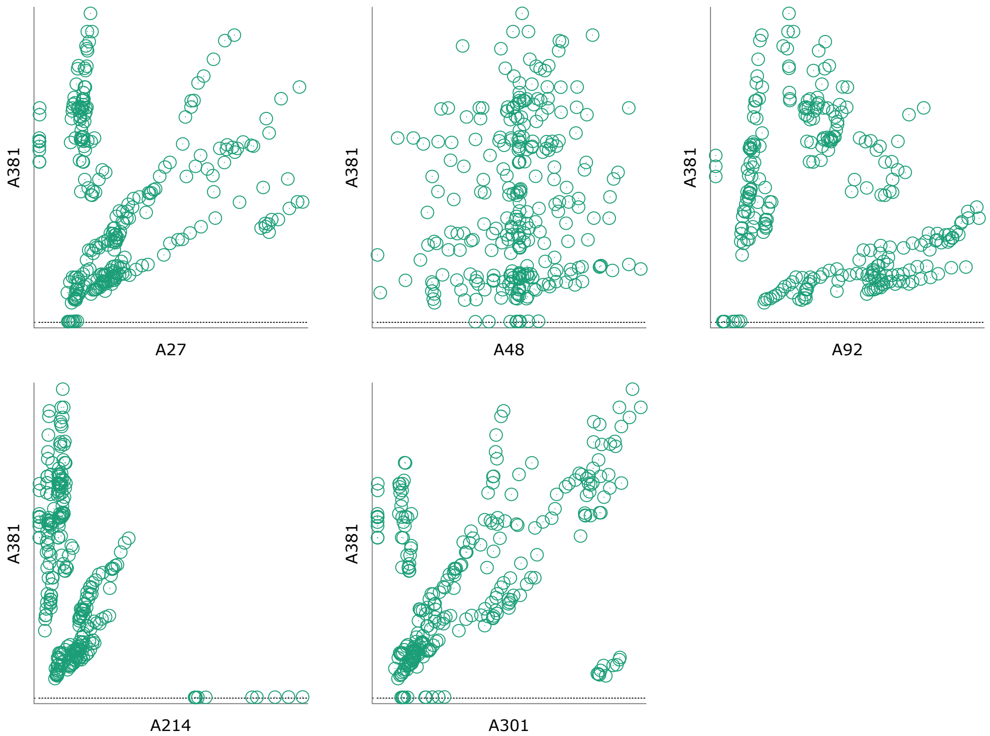


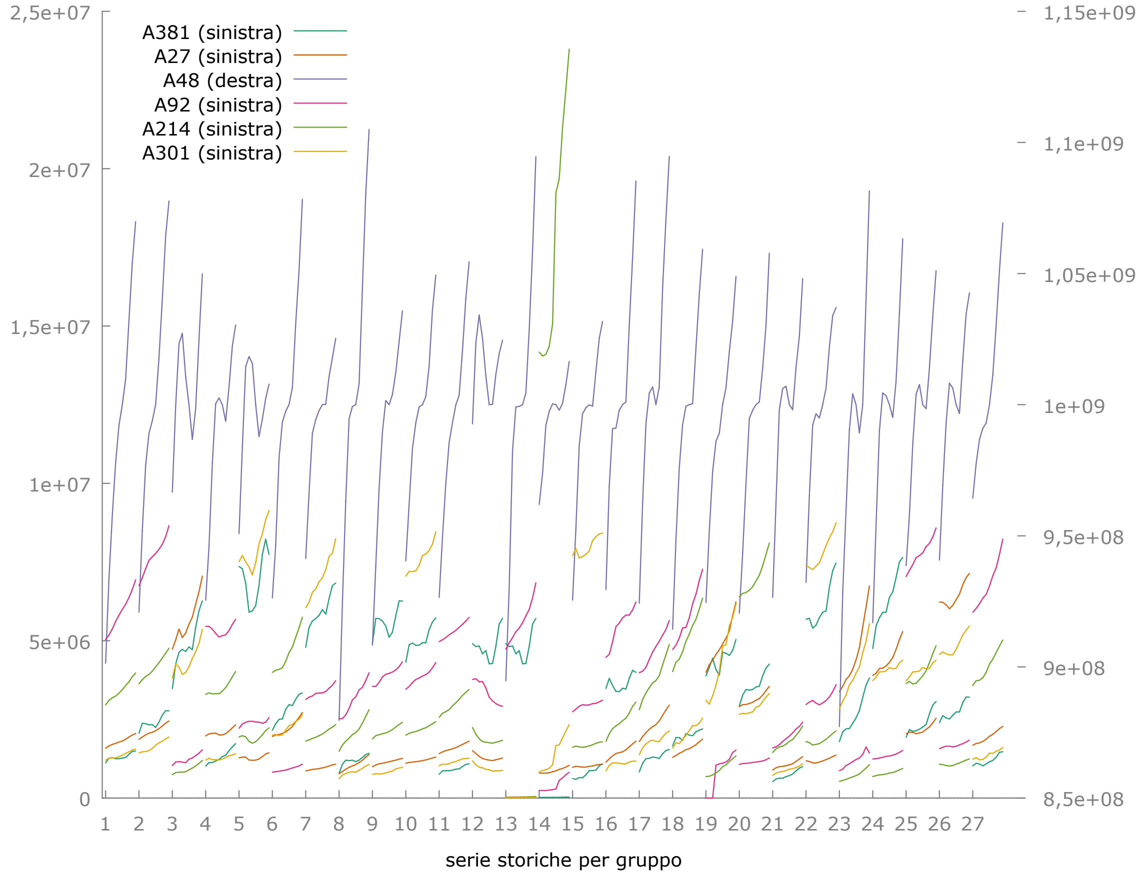
Statistiche descrittive, usando le osservazioni 1:01 - 27:10

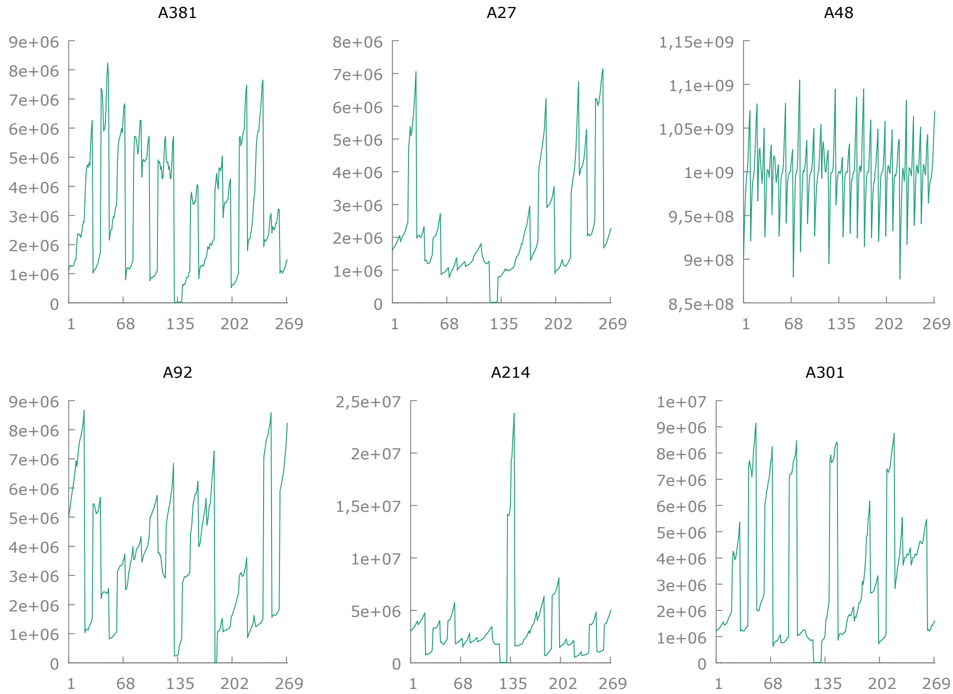
Variabile	Media	Mediana	Minimo	Massimo
A381	3,1833e+006	2,7751e+006	17512,	8,2253e+006
A27	2,2102e+006	1,6848e+006	14487,	7,1380e+006
A48	9,9835e+008	1,0000e+009	8,7726e+008	1,1050e+009
A92	3,6062e+006	3,3631e+006	0,87010	8,6590e+006
A214	3,1556e+006	2,1931e+006	27431,	2,3801e+007
A301	3,1837e+006	2,0365e+006	11328,	9,1381e+006
Variabile	SQM	Coeff. di variazione	Asimmetria	Curtosi
A381	2,0519e+006	0,64457	0,36293	-0,99768
A27	1,6158e+006	0,73108	1,3914	1,0952
A48	3,8215e+007	0,038278	-0,31092	0,76325
A92	2,1970e+006	0,60923	0,36128	-0,88968
A214	3,3670e+006	1,0670	3,6580	16,072
A301	2,5338e+006	0,79586	0,82645	-0,64042
Variabile	5% Perc.	95% Perc.	Range interquartile	Osservazioni mancanti

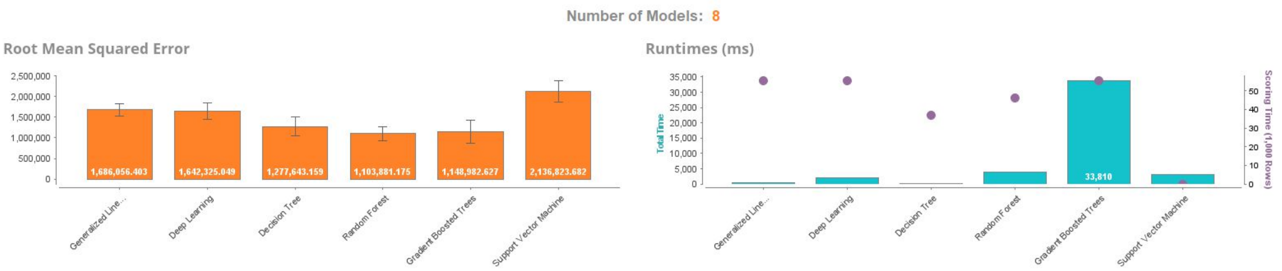
A381	6,1295e+005	6,7566e+006	3,5757e+006	0
A27	7,9287e+005	6,1317e+006	1,2935e+006	0
A48	9,2549e+008	1,0611e+009	3,2596e+007	0
A92	8,2049e+005	7,6832e+006	3,8458e+006	0
A214	6,1554e+005	7,2175e+006	2,2038e+006	0
A301	7,4405e+005	8,0727e+006	3,4359e+006	0

```
Analisi delle componenti principali
n = 270

Analisi degli autovalori della matrice di correlazione

Componente  Autovalore   Proporzione   Cumulata
    1        2,0025       0,3337        0,3337
    2        1,2191       0,2032        0,5369
    3        1,0704       0,1784        0,7153
    4        0,8720       0,1453        0,8607
    5        0,5132       0,0855        0,9462
    6        0,3228       0,0538        1,0000

Autovettori (pesi della componente)

                 PC1       PC2       PC3       PC4       PC5       PC6
A381           0,540     0,310    -0,088    -0,258     0,554    -0,481
A27            0,393    -0,331     0,365     0,620    -0,213    -0,416
A48            0,059     0,382     0,846    -0,061     0,128     0,338
A92           -0,365     0,679    -0,018     0,147    -0,382    -0,488
A214          -0,384    -0,430     0,377    -0,536     0,002    -0,488
A301           0,519     0,044    -0,015    -0,487    -0,697     0,073
```


A381
A27
A381
A48
A381
A92
A381
A214
A381
A301


2,5e+07
2e+07
1,5e+07
1e+07
5e+06
0
1,15e+09
1,1e+09
1,05e+09
1e+09
9,5e+08
9e+08
8,5e+08
A381 (sinistra)
A27 (sinistra)
A48 (destra)
A92 (sinistra)
A214 (sinistra)
A301 (sinistra)
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27
serie storiche per gruppo





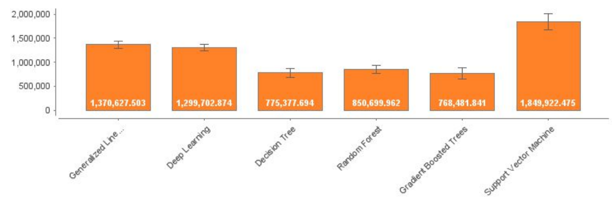
Root Mean Squared Error ▼

Model	Root Mean Squared Err...	Standard Deviation	Gains	Total Time	Training Time (1,000 R...	Scoring Time (1,000 Ro...	Deploy
Generalized Linear Model	1,686,056.403	± 150,896.834	?	391 ms	178 ms	56 ms	Deploy
Deep Learning	1,642,325.049	± 200,534.844	?	2 s	2 s	56 ms	Deploy
Decision Tree	1,277,643.159	± 224,741.732	?	203 ms	15 ms	37 ms	Deploy
Random Forest	1,103,881.175	± 174,548.005	?	4 s	33 ms	46 ms	Deploy
Gradient Boosted Trees	1,148,982.627	± 279,044.898	?	34 s	2 s	56 ms	Deploy
Support Vector Machine	2,136,823.682	± 263,108.154	?	3 s	326 ms	~0 ms	Deploy

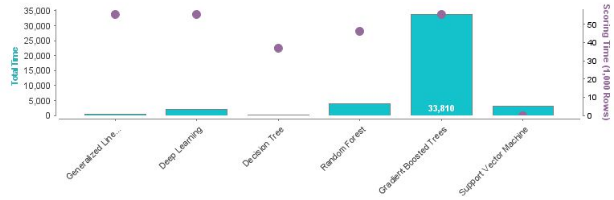
Overview

Number of Models: 8

Absolute Error



Runtimes (ms)



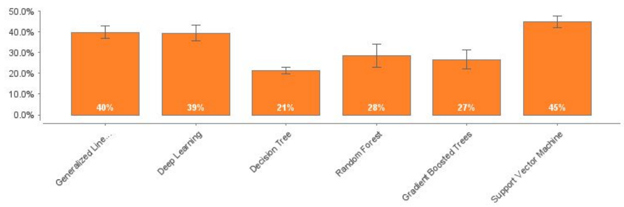
Absolute Error

Model	Absolute Error	Standard Deviation	Gains	Total Time	Training Time (1,000 R...	Scoring Time (1,000 Ro...	Deploy
Generalized Linear Model	1,370,627.503	± 76,254.615	?	391 ms	178 ms	56 ms	Deploy
Deep Learning	1,299,702.874	± 65,588.521	?	2 s	2 s	56 ms	Deploy
Decision Tree	775,377.694	± 90,569.423	?	203 ms	15 ms	37 ms	Deploy
Random Forest	850,699.962	± 85,239.321	?	4 s	33 ms	46 ms	Deploy
Gradient Boosted Trees	768,481.841	± 115,208.261	?	34 s	2 s	56 ms	Deploy
Support Vector Machine	1,849,922.475	± 170,265.163	?	3 s	326 ms	~0 ms	Deploy

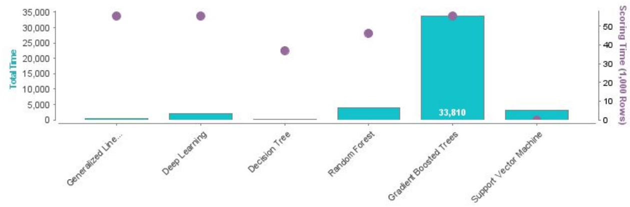
Overview

Number of Models: 8

Relative Error



Runtimes (ms)



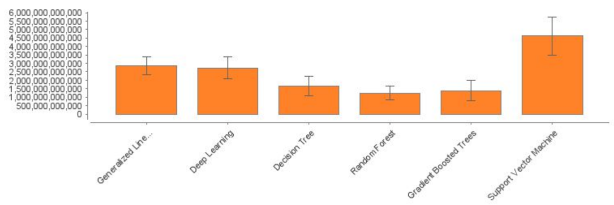
Relative Error

Model	Relative Error ↑	Standard Deviation	Gains	Total Time	Training Time (1,000 R...	Scoring Time (1,000 Ro...	Deploy
Decision Tree	21.3%	± 1.8%	?	203 ms	15 ms	37 ms	Deploy
Gradient Boosted Trees	26.6%	± 4.6%	?	34 s	2 s	56 ms	Deploy
Random Forest	28.4%	± 5.5%	?	4 s	33 ms	46 ms	Deploy
Deep Learning	39.3%	± 3.8%	?	2 s	2 s	56 ms	Deploy
Generalized Linear Model	39.8%	± 3.1%	?	391 ms	178 ms	56 ms	Deploy
Support Vector Machine	45.0%	± 2.9%	?	3 s	326 ms	~0 ms	Deploy

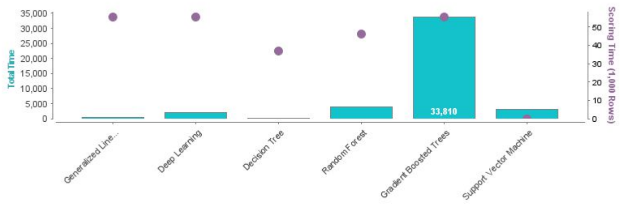
Overview

Number of Models: 8

Squared Error



Runtimes (ms)



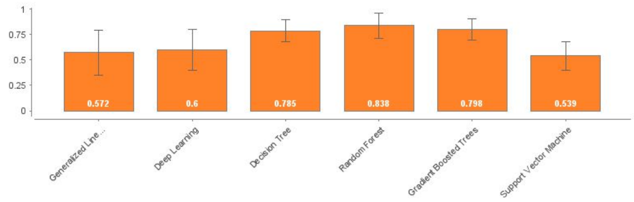
Squared Error

Model	Squared Error ↑	Standard Deviation	Gains	Total Time	Training Time (1,000 R...	Scoring Time (1,000 Ro...	Deploy
Random Forest	1,242,927,254,008.813	± 397,329,384,988.811	?	4 s	33 ms	46 ms	Deploy
Gradient Boosted Trees	1,382,453,921,385.634	± 594,958,911,624.599	?	34 s	2 s	56 ms	Deploy
Decision Tree	1,672,779,117,598.615	± 583,387,506,476.484	?	203 ms	15 ms	37 ms	Deploy
Deep Learning	2,729,402,943,935.536	± 648,500,323,315.737	?	2 s	2 s	56 ms	Deploy
Generalized Linear Model	2,861,002,077,360.314	± 516,807,925,450.935	?	391 ms	178 ms	56 ms	Deploy
Support Vector Machine	4,621,396,167,810.999	± 1,143,363,116,519.999	?	3 s	326 ms	~0 ms	Deploy

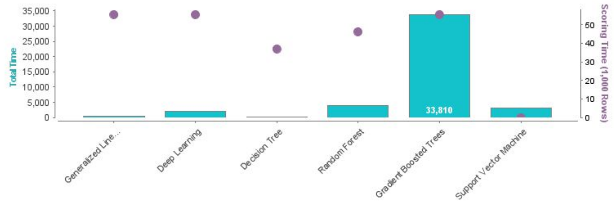
Overview

Number of Models: 8

Correlation



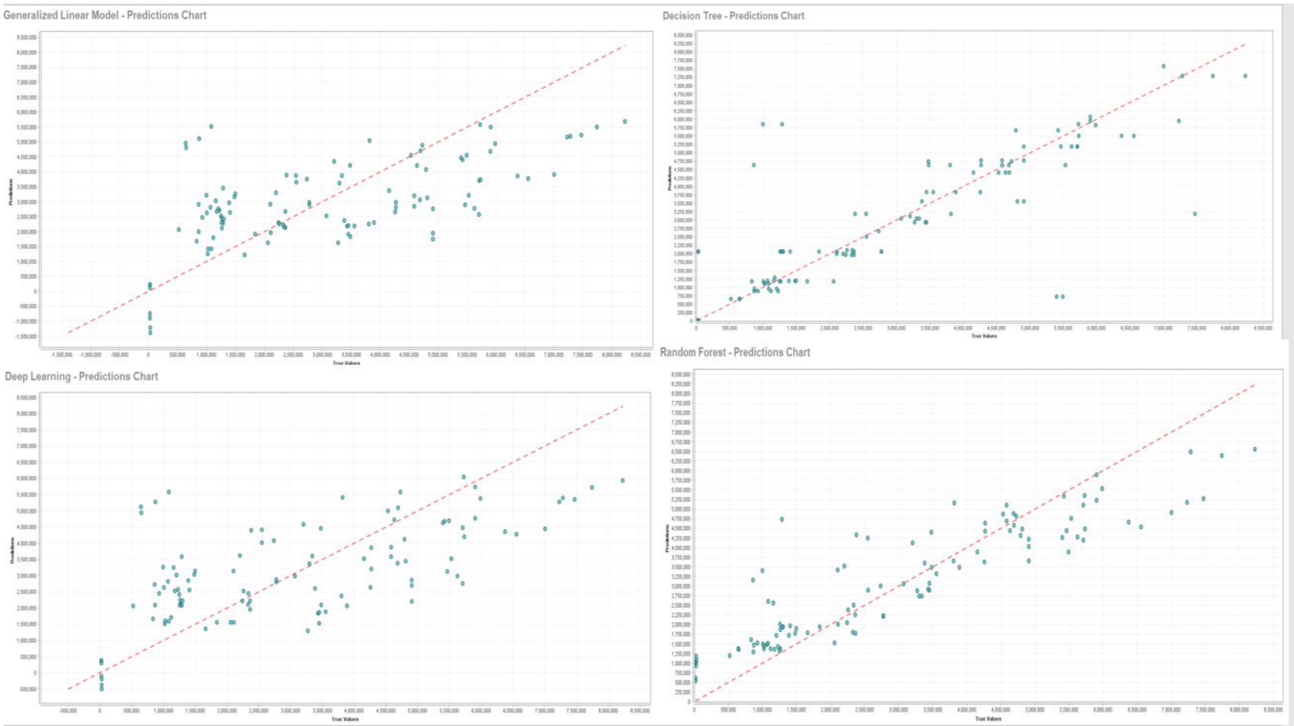
Runtimes (ms)



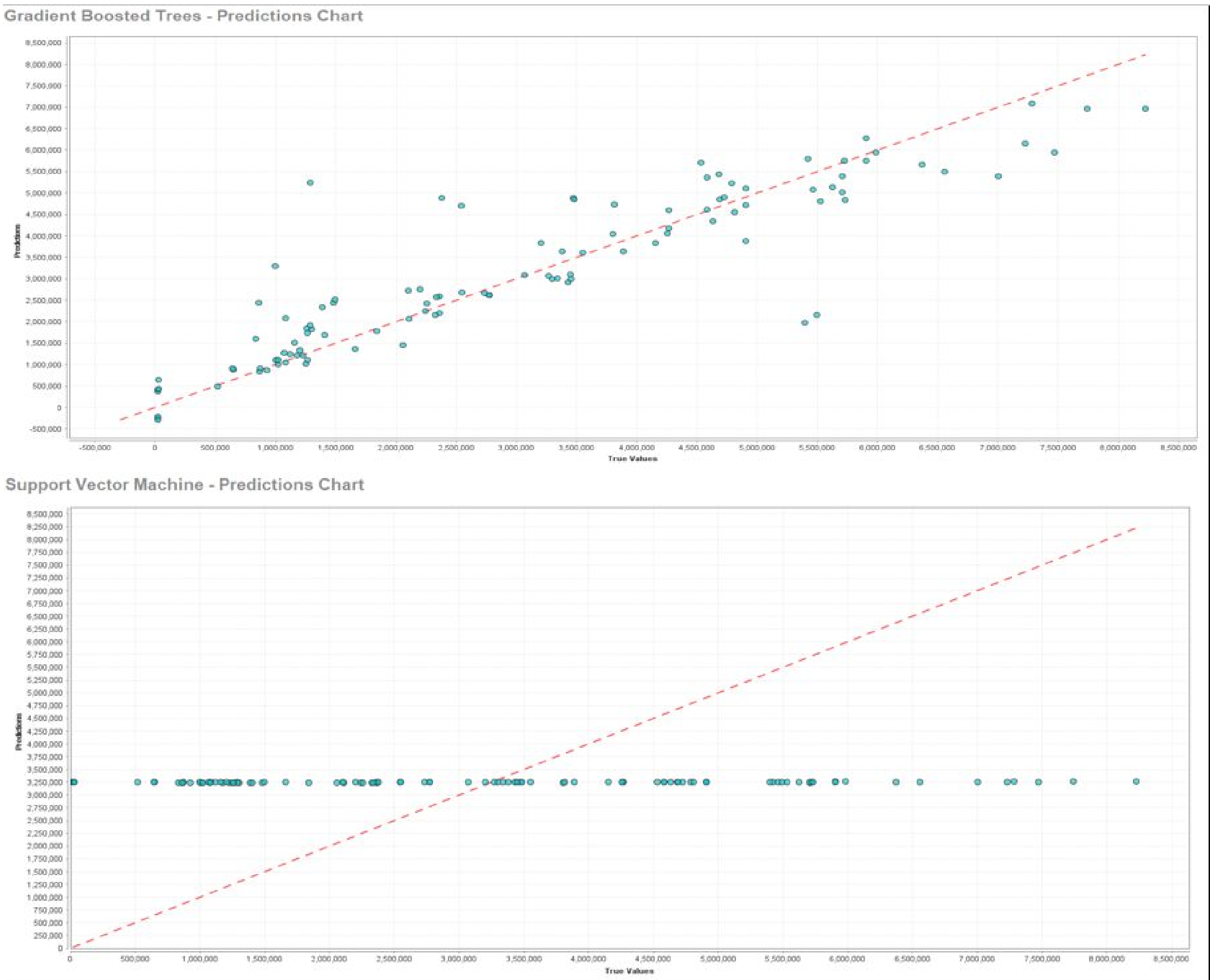
Correlation ▾

Model	Correlation ↑	Standard Deviation	Gains	Total Time	Training Time (1,000 R...	Scoring Time (1,000 Ro...	Deploy
Support Vector Machine	0.539	± 0.143	?	3 s	326 ms	~0 ms	Deploy
Generalized Linear Model	0.572	± 0.221	?	391 ms	178 ms	56 ms	Deploy
Deep Learning	0.6	± 0.2	?	2 s	2 s	56 ms	Deploy
Decision Tree	0.785	± 0.109	?	203 ms	15 ms	37 ms	Deploy
Gradient Boosted Trees	0.798	± 0.106	?	34 s	2 s	56 ms	Deploy
Random Forest	0.838	± 0.125	?	4 s	33 ms	46 ms	Deploy

```
Deep Learning Model
Model Metrics Type: Regression
 Description: Metrics reported on full training frame
 model id: rm-h2o-model-production_model-4
 frame id: rm-h2o-frame-production_model-4
 MSE: 2.04807379E12
 RMSE: 1431109.2
 R^2: 0.5117368
 mean residual deviance: 2.04807379E12
 mean absolute error: 1124933.8
 root mean squared log error: NaN
Status of Neuron Layers (predicting A381, regression, gaussian distribution, Quadratic loss, 2,951 weights/biases, 39.6 KB, 2,700 training samples, mini-batch size 1):
 Layer Units      Type Dropout       L1       L2 Mean Rate Rate RMS Momentum Mean Weight Weight RMS Mean Bias Bias RMS
     1     6     Input  0.00 %
     2    50 Rectifier       0 0.000010 0.000000  0.003086 0.002767 0.000000    0.013451   0.194158  0.486768 0.025553
     3    50 Rectifier       0 0.000010 0.000000  0.008652 0.018992 0.000000   -0.003374   0.139512  0.993265 0.021346
     4     1    Linear         0.000010 0.000000  0.000344 0.000197 0.000000    0.023444   0.204346 -0.009679 0.000000
Scoring History:
           Timestamp   Duration Training Speed   Epochs Iterations     Samples Training RMSE   Training Deviance  Training MAE Training r2
 2021-06-20 17:38:46  0.000 sec                 0.00000          0    0.000000           NaN                 NaN           NaN         NaN
 2021-06-20 17:38:46  0.049 sec  10800 obs/sec  1.00000          1  270.000000 1642983.34892 2699394284838.58250 1300491.61069     0.35646
 2021-06-20 17:38:46  0.085 sec   9642 obs/sec  2.00000          2  540.000000 1635576.96143 2675111996771.89750 1244762.85022     0.36225
 2021-06-20 17:38:46  0.119 sec   9529 obs/sec  3.00000          3  810.000000 1578342.82895 2491166085708.61430 1209091.52134     0.40610
 2021-06-20 17:38:46  0.151 sec   9908 obs/sec  4.00000          4 1080.000000 1583731.43088 2508205245159.88230 1261162.45010     0.40204
 2021-06-20 17:38:46  0.183 sec  10150 obs/sec  5.00000          5 1350.000000 1523958.49036 2322449480336.88870 1198178.45722     0.44633
 2021-06-20 17:38:46  0.217 sec  10188 obs/sec  6.00000          6 1620.000000 1516681.10833 2300321584374.22000 1188091.42060     0.45160
 2021-06-20 17:38:46  0.252 sec  10216 obs/sec  7.00000          7 1890.000000 1506930.68211 2270840080674.06450 1150331.79467     0.45863
 2021-06-20 17:38:46  0.284 sec  10236 obs/sec  8.00000          8 2160.000000 1468025.31983 2155098339656.24540 1170467.12183     0.48622
 2021-06-20 17:38:46  0.321 sec  10296 obs/sec  9.00000          9 2430.000000 1447426.04096 2095042144053.34030 1126069.82146     0.50054
 2021-06-20 17:38:46  0.367 sec  10112 obs/sec 10.00000         10 2700.000000 1431109.29427 2048073812150.48440 1124933.79206     0.51174

H2O version: 3.30.0.1-rm9.8.1
```



Predictive ability of Generalized Linear Model, Decision Tree, Deep Learning, Random Forest.



The predictive ability of Gradient Boosted Trees and Support Vector Machine.