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DIPARTIMENTO DI INGEGNERIA MECCANICA E AEROSPAZIALE

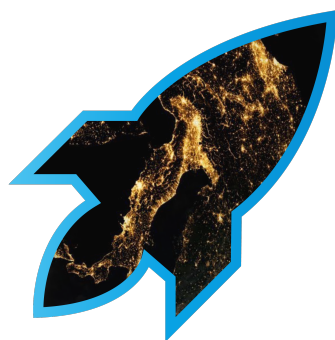
UNIVERSITÀ DI ROMA LA SAPIENZA

CORSO DI INGEGNERIA MECCANICA

SUBJECT

TITLE

SUBTITLE



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ABSTRACT

The aim of the project is to analyse the data from the "New York City Airbnb Open Data" from the Kaggle website.

In particular, we focus on the developing of predictive model to forecast the house' prices using Supervised Learning algorithms:

- Random Forest
- Ranger Random Forest
- Linear Regression
- Neural Newtworks (?)

A crucial part of the project was to the tuning and finding of the hyperparameters of the different models in order to get the best fit.

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GOAL

The goal is developing different models in order to predict the price of a house in New York.

The dataset has different columns:

- **id**
- **name**: name of the listing
- **host_id**
- **host_name**
- **neighbourhood_group**: location
- **neighbourhood**: area
- **latitude**: coordinates
- **longitude**: coordinates
- **room_type**: space type
- **price**: in dollars
- **minimum_nights**: amount of nights minimum
- **number_of_reviews**: number of reviews
- **last_review**: latest review
- **reviews_per_month**: number of reviews per month
- **calculated_host_listings_count**: amount of listing per host

- **availability_365**: number of days when listing is available for booking

We select just 5 of this feature from the dataset since we denotes them as the most important for the price of a house: latitude, longitude, room type, neighbourhood and the price itself to compare the prediction during the tests.

RESULTS

- 3.1 RANDOM FOREST RESULTS
- 3.2 RANGER RANDOM FOREST RESULTS
- 3.3 LINEAR REGRESSION RESULTS
- 3.4 NEURAL NETWORKS RESULTS

CONCLUSION

APPENDIX

TABELLE E GRAFICI

Here a few examples of tables and graphs.

6.1 TABELLE

<i>Codice</i>	<i>CdL</i>	<i>Lotto</i>	$T_{\text{setup/lotto}}$	$T_{\text{lav/pezzo}}$	$T_{\text{proc/pezzo}}$	<i>Quantità</i>	T_{tot}
100	4	250	25	0,5	0,6	1	0,6
111	2	250	20	2	2,08	1	2,08
111	3	250	15	1,5	1,56	1	1,56
112	2	250	20	2,5	2,58	1	2,58
112	3	250	15	2	2,06	1	2,06
113	3	500	15	1	1,03	2	2,06
120	1	50	30	2	2,6	0,1	0,26
121	1	25	30	3	4,2	0,1	0,42
121	1	25	30	2,5	3,7	0,1	0,37

6.1.1 ALTRA TABELLA

6.2 GRAFICI

6.2.1 ALTRO GRAFICO

FORMULE

Se non sono ammesse consegne in ritardo siamo in presenza di un problema con Backlog. Sia t_i il periodo in cui non si è in backlog e t_b il periodo di backlog. Essendo $t_i = (Q - B)/D$, avremo:

$$\text{Costi di ordinazione} = C \cdot D/Q$$

$$\text{Costi di mantenimento} = H \cdot (Q - B)/2 \cdot t_i/T = H \cdot (Q - B)^2/2Q$$

$$\text{Costi di backorder} = C_b \cdot B \cdot t_b/2T = C_b \cdot B^2/2Q$$

$$\text{Costi variabili totali} = TC(Q) = C \cdot D/Q + H \cdot (Q - B)^2/2Q + C_b \cdot B^2/2Q$$

$$\text{Condizioni di minimo: } \begin{cases} \frac{\partial TC}{\partial Q} = 0 \\ \frac{\partial TC}{\partial B} = 0 \end{cases} \Rightarrow Q^* = \sqrt{\frac{2C \cdot D(H + C_b)}{H \cdot C_b}} = EOQ \sqrt{\frac{H + C_b}{C_b}}$$

ALTRO

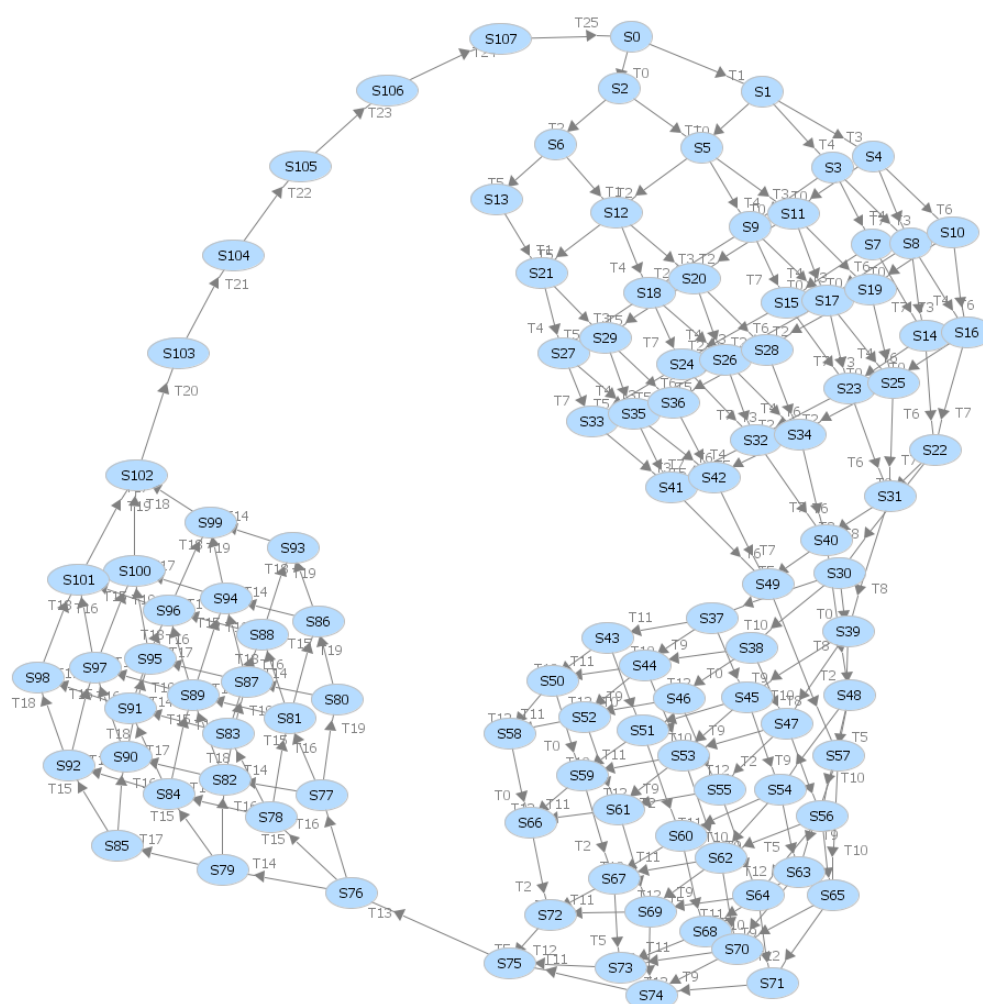


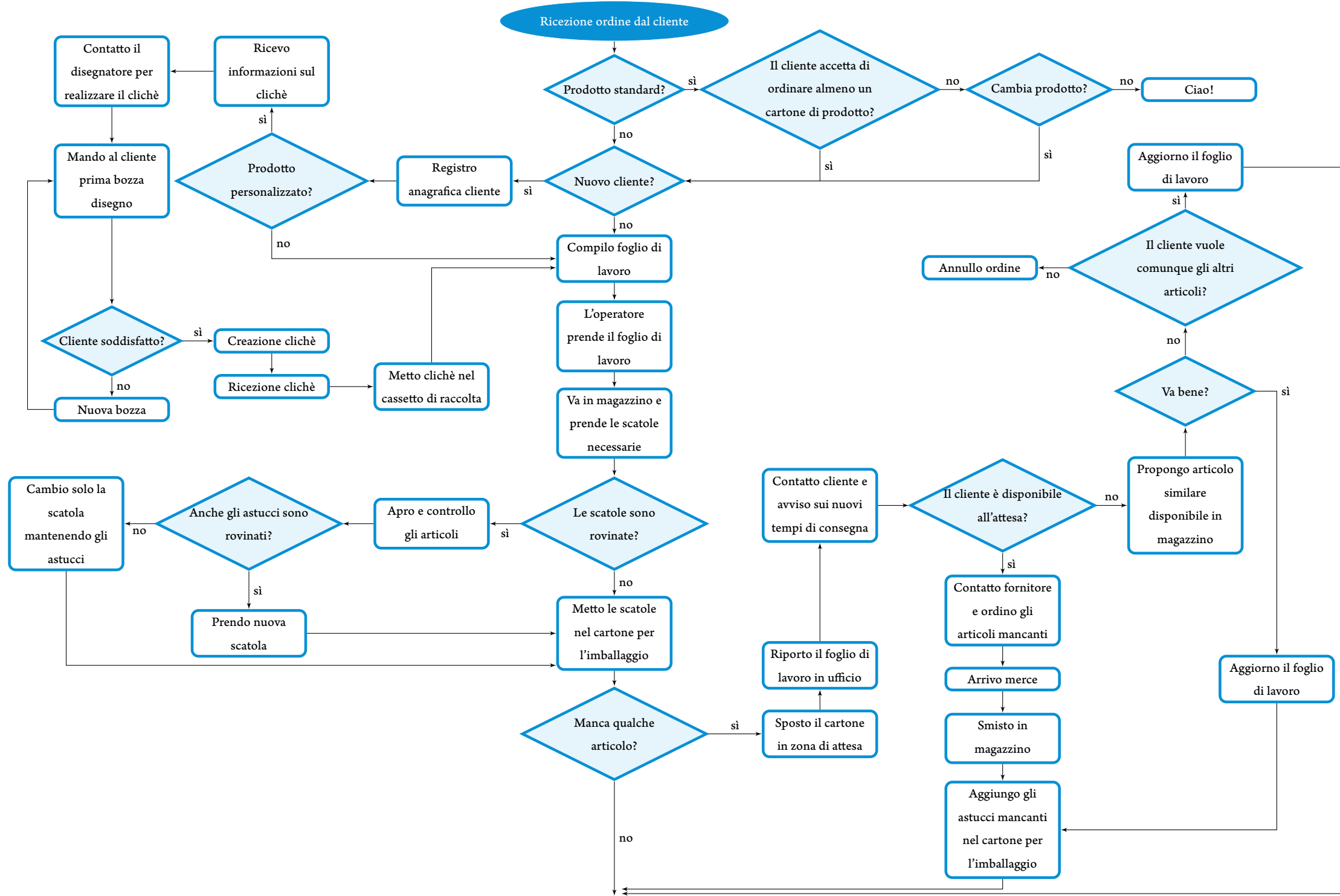
Figure 1: Didascalia.

8.1 FOOTNOTE

You can create a footnote like this.¹

8.2 FLOWCHART

¹I created a footnote.



REFERENCES

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