Politecnico di Milano
School of Industrial and Information Engineering

Data Mining and Text Mining

January 18, 2020

NAME

CODICE PERSONA/ID

GENERAL INSTRUCTIONS

- **Answers must be clearly written inside the answer box designated for each problem.**
- **All the answers must be adequately motivated.**
- **Pencils are not allowed. The exam consists of 6 sheets of paper. It must be returned with all the 6 sheets. No any other sheet can be added. No sheet can be removed.**
- **This is a closed-book/closed-notes exam.**
- **Only non-programmable calculators are allowed.**
- **Notes/books/mobile phones are not allowed.**
- **If you are caught using forbidden material, the exam will immediately end and an RP grade will be recorded; then, your Data Mining exam will consist of an oral examination from then on.**

COURSE PROJECT SCORE

FINAL TIME

GRADES

1	2	3
4	5	6

SCORING

- **A problem left unsolved will amount to zero points.**
- **A completely wrong solution will amount to -3 points**

STUDENTS WHO DID THE COURSE PROJECT HAVE 1:40h TO SOLVE PROBLEMS 1, 2, 3, AND 4

ALL THE OTHER STUDENTS HAVE 2:20h TO SOLVE ALL THE SIX PROBLEMS

Problem 1 (6 points). Consider a dataset containing the information about a bike sharing service which records the following ten attributes:

- timestamp: the day of the year and the hour of the day
- cnt: number of bikes
- t1: actual temperature
- t2: temperature as it feels
- hum: humidity %
- wind_speed: km/h
- weather_code: a number describing a weather condition (no other information provided)
- is_holiday: 1 if it is a holiday, 0 otherwise
- is_weekend: 1 if it is a weekend day, 0 otherwise
- season: a number encoding the season

Consider the following example rows and the attribute description printed by describe command. Attribute **cnt** is your target variable. The final objective is to build a model to predict the number of bikes (attribute **cnt**) used in a given hour of a given day.

```
df = pd.read_csv("london_merged.csv")
df.head(5)
```

	timestamp	cnt	t1	t2	hum	wind_speed	weather_code	is_holiday	is_weekend	season
0	2015-01-04 00:00:00	182	3.0	2.0	93.0	6.0	3.0	0.0	1.0	3.0
1	2015-01-04 01:00:00	138	3.0	2.5	93.0	5.0	1.0	0.0	1.0	3.0
2	2015-01-04 02:00:00	134	2.5	2.5	96.5	0.0	1.0	0.0	1.0	3.0
3	2015-01-04 03:00:00	72	2.0	2.0	100.0	0.0	1.0	0.0	1.0	3.0
4	2015-01-04 04:00:00	47	2.0	0.0	93.0	6.5	1.0	0.0	1.0	3.0

```
df.describe()
```

	cnt	t1	t2	hum	wind_speed	weather_code	is_holiday	is_weekend	season
count	17414.000000	17414.000000	17414.000000	17414.000000	17414.000000	17414.000000	17414.000000	17414.000000	17414.000000
mean	1143.101642	12.468091	11.520836	72.324954	15.913063	2.722752	0.022051	0.285403	1.492075
std	1085.108068	5.571818	6.615145	14.313186	7.894570	2.341163	0.146854	0.451619	1.118911
min	0.000000	-1.500000	-6.000000	20.500000	0.000000	1.000000	0.000000	0.000000	0.000000
25%	257.000000	8.000000	6.000000	63.000000	10.000000	1.000000	0.000000	0.000000	0.000000
50%	844.000000	12.500000	12.500000	74.500000	15.000000	2.000000	0.000000	0.000000	1.000000
75%	1671.750000	16.000000	16.000000	83.000000	20.500000	3.000000	0.000000	1.000000	2.000000
max	7860.000000	34.000000	34.000000	100.000000	56.500000	26.000000	1.000000	1.000000	3.000000

As the very first step, you are asked to preprocess the data and build the best **four new features** (computed using the ten existing ones) that can help building a better model for **cnt**.

Question #1: For each new feature specify (1) how the new feature is computed from the existing attributes, (2) how it improves the available information, (3) why it might help building a better the predictive model for **cnt.**

Question #2: After the new features have been computed, would you still keep all the original features? If yes, why? If not, which variables would you eliminate?

Problem 1 (continued).

Feature #1
How is the new feature computed from the existing attributes?
How does it improve the available information?
Why might it help building a better the predictive model for cnt?

Feature #2
How is the new feature computed from the existing attributes?
How does it improve the available information?
Why might it help building a better the predictive model for cnt?

Feature #3
How is the new feature computed from the existing attributes?
How does it improve the available information?
Why might it help building a better the predictive model for cnt?

Feature #4
How is the new feature computed from the existing attributes?
How does it improve the available information?
Why might it help building a better the predictive model for cnt?

Solution Problem #1:

Question #1: We know very few things about the data. We know how they look like (from the head command, and we know some stats from the describe command. Nothing else. We don't know what regression methods will be used. We don't know correlation properties; we don't know to what the encoding of season and weather_code represents. Maybe there is a meaningful order so there is not much we can do without additional information. Surely, the timestamp contains a lot of information that is useless as it is. The column is a primary key so it is a source of overfitting and cannot be used by methods that cannot deal with categorical variables.

We can split the timestamp in several variables

1. We can create a column year since maybe the behavior changes from year to year based on the number of bikes available. Surely it might be useful and improves the data by extracting information that was present but previously useless.
2. We can create a column month that improves over an encoding of season. Different months in the same season might have different behavior. It might be useful and improves the data by extracting information that was present but previously useless.
3. We can create a column with the hour since bike rental might change according to the time of the day. Again, it improves the data by extracting information that was present but previously useless.
4. We can create a column with the day of the week (Monday=1, 2, 3, 4, ..., Sunday=7) since the rental behavior might be different between the single working days. In addition, we have the information about weekends, but the behavior might change before Saturdays and Sundays. Again, it improves the data by extracting information that was present but previously useless.
5. We can create a column t1-t2 since the difference in perceived temperature might be important. Note that we use the raw difference which is positive if the reported temperature is higher than the perceived temperature and negative otherwise.

Question #2: Timestamp must be eliminated. It is a primary key and the source of overfitting and cannot be used by methods that cannot deal with categorical attribute and obviously one-hot-encoding cannot be employed.

Problem 2 (6 points).

(1) Write the pseudocode of agglomerative hierarchical clustering given the data D containing N data points described by d attributes

(2) Compare Hierarchical Clustering and k-Means in terms of their computational complexity

Notes: Write one instruction per line. The function definition is specified using Python notation just for your convenience.

ALGORITHM 14.1. Agglomerative Hierarchical Clustering Algorithm

AGGLOMERATIVECLUSTERING($\mathbf{D}, k$):

1 $\mathcal{C} \leftarrow \{C_i = \{\mathbf{x}_i\} \mid \mathbf{x}_i \in \mathbf{D}\}$ // Each point in separate cluster
2 $\Delta \leftarrow \{\delta(\mathbf{x}_i, \mathbf{x}_j) : \mathbf{x}_i, \mathbf{x}_j \in \mathbf{D}\}$ // Compute distance matrix
3 **repeat**
4 Find the closest pair of clusters $C_i, C_j \in \mathcal{C}$
5 $C_{ij} \leftarrow C_i \cup C_j$ // Merge the clusters
6 $\mathcal{C} \leftarrow (\mathcal{C} \setminus \{C_i, C_j\}) \cup \{C_{ij}\}$ // Update the clustering
7 Update distance matrix Δ to reflect new clustering
8 **until** $|\mathcal{C}| = k$

Hierarchical Clustering:
Time and Space Requirements

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- $O(N^2)$ space since it uses the proximity matrix.
  - N is the number of points.
- $O(N^3)$ time in many cases
  - There are N steps and at each step the size, N^2, proximity matrix must be updated and searched
  - Complexity can be reduced to $O(N^2 \log(N))$ time for some approaches

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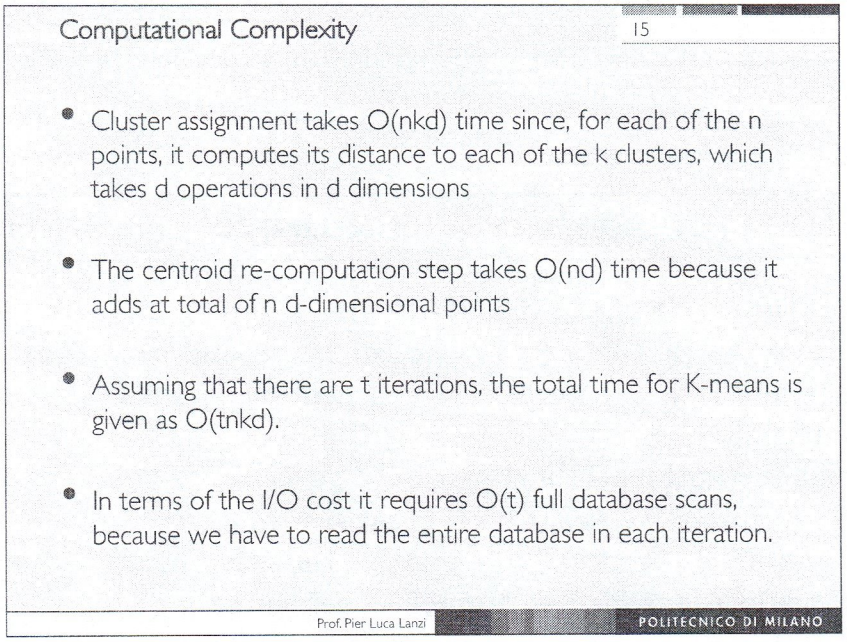
Problem 2 (Continued).

For k-means we have:



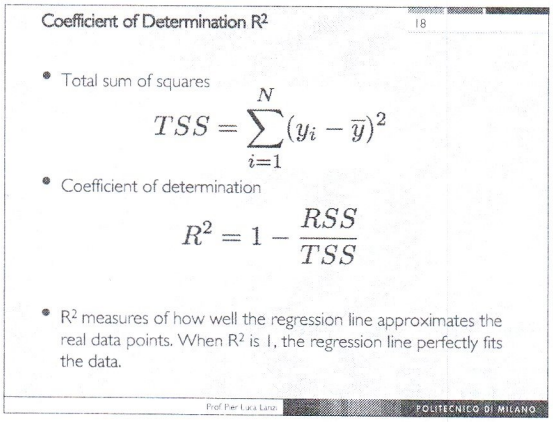
Problem 3 (6 points). Suppose the bike sharing data discussed in the first problem have been adequately preprocessed. It is now time to build some models. For this purpose, you apply ten-fold crossvalidation on the training data (the only data you have) to evaluate the performance of four regression approaches:

- Multivariate linear regression
- Lasso regression
- K-Nearest Neighbor regression with a k equal to 5
- Random forests with 100 trees

You apply ten-fold crossvalidation and record the following results:

```
Linear Regression           R2 Average=0.44 Std Dev=0.02
Lasso Regression            R2 Average=0.44 Std Dev=0.02
KNN Regression              R2 Average=0.82 Std Dev=0.01
Random Forest Regression    R2 Average=0.96 Std Dev=0.00
```

Question #1 (1 point): What is R2? How is it computed? What does it indicate?



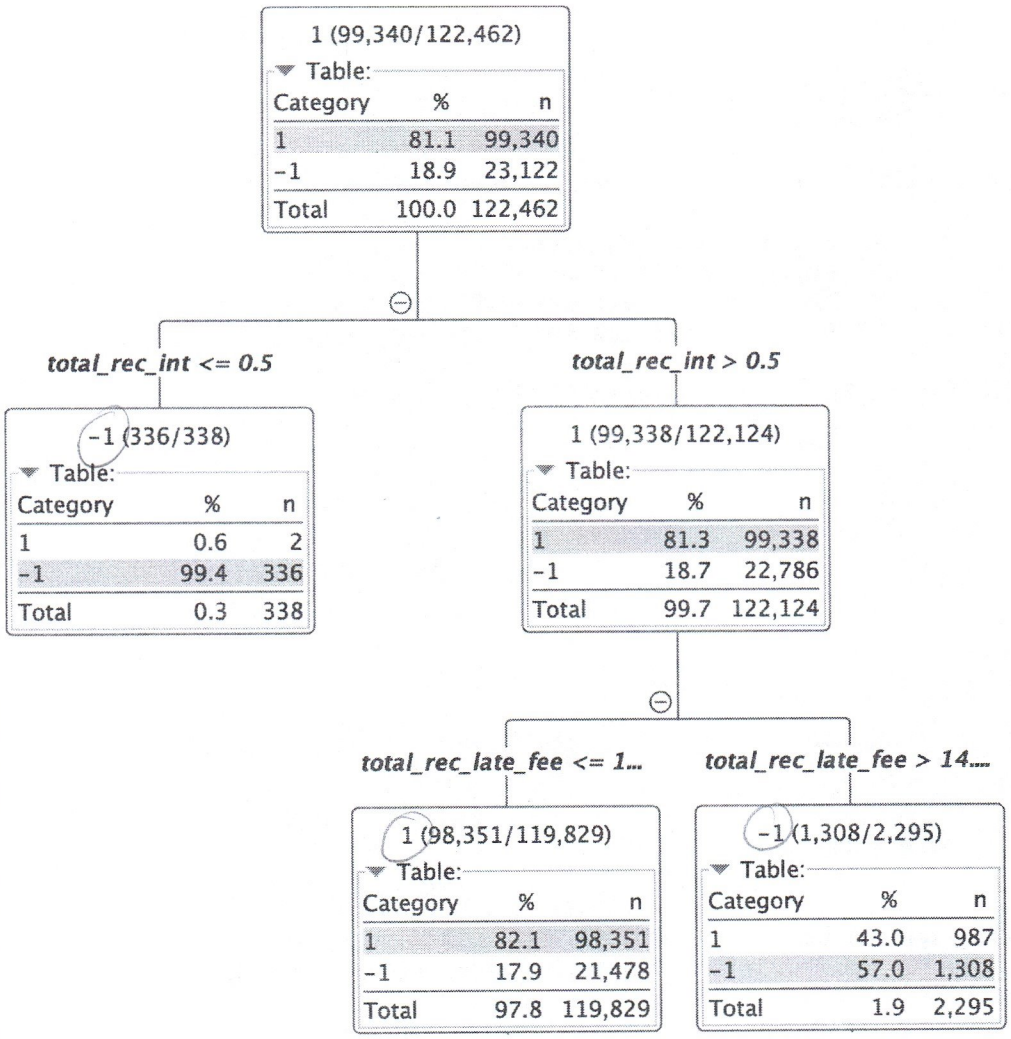
Question #2 (3 points): You are asked to comment the results above and to suggest some interesting findings about the nature of the problem at hand. What would you say about the problem given the performance of the regressors?

The question asks to discuss findings about the problem at hand. So, what do the result suggest about the problem. To answer this, we should consider the type of models that all the methods build. As can be noted from the performance reported global linear models (multivariate linear regression and lasso regression) have a poor performance. This suggests that the number of bikes in a given day cannot be modeled as a linear relation involving all the data. On the other hand, locality appears to be important in this problem, in fact k-nearest neighbor has a much better performance than linear models. And this is also suggested by the results on random forests which are made of trees that isolates problem subspaces and build a simple local model for each subspace. **Extra Comment:** This is kind of make sense if you consider the problem, if I like to take a bike to work when it is sunny or I usually take a bike during the weekends, the days I will take a bike are very similar to each other so similarity between days is likely to be important. The results above support this.

Question #3 (2 points): How would you compute the final model to deploy in production?

Random forests clearly perform better and the results are quite robust. Per se, random forests don't overfit and in this case cross-validation was applied so we can trust the reported performance. Thus, we retrain the random forest with all the data available, in this case, the training set.

Problem 4 (6 points). Given the following decision tree, compute the confusion matrix, the accuracy, the precision, and the recall. For the computation consider 1 represents the positive class and -1 represents the negative class. Note that the comma "," is the thousands separator; for example: 1,234 represents 1234.



Question #1: Compute the confusion matrix on the data used to build the decision tree.

		Predicted Class	
		1	**-1**
True Class	**1**	**98351**	**989**
	-1	**21478**	**1644**

Problem 4 (Continued).

Question #2: Show the formula to compute accuracy and compute the accurary from the confusion matrix above.

Accuracy = (TP+TN)/(TP+TN+FP+FN) = 99995/122462 = 0.82

Question #3: Show the formula to compute precision and compute the precision from the confusion matrix above.

$$Precision(p) = \frac{TP}{TP + FP}$$

Precision = 98351/(98351+21478) = 0.82

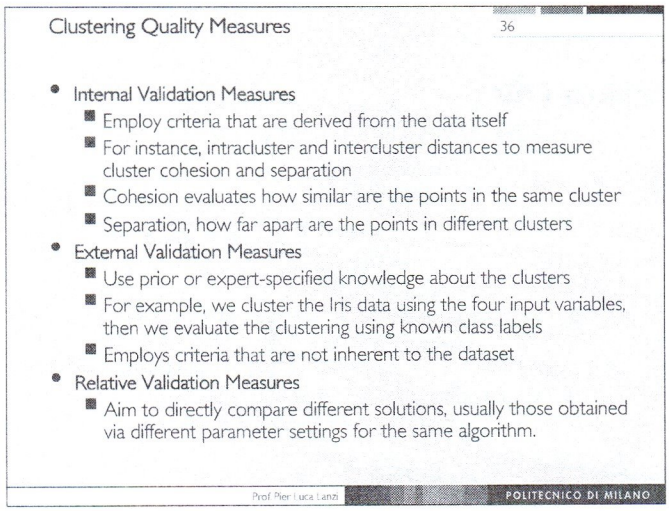
Question #4: Show the formula to compute recall and compute the recall from the confusion matrix above.

$$Recall(r) = \frac{TP}{TP + FN}$$

Recall = 98351/(98351+989) = 0.99

Problem 5 (6 points). In the context of clustering, answer the following questions.

Question #1: Define internal validation measures and provide an example.

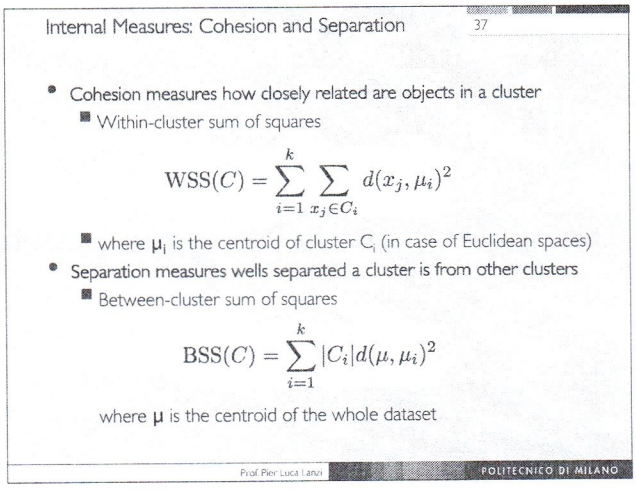


WSS and BSS are internal validation measures.

Question #2: Define external validation measures and provide an example.

An example of external validation measures is the validation against existing labels.

Question #3: What are cohesion and separation measures?



Problem 6 (3 points). Define autocorrelation in the context of data series.

Definition from the notebooks on data series.