Easier Data Preprocessing in PostgreSQL

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Outline

- Introduction to our project
- Implemented functions
 - Missing values filling
 - Feature selection for regression and classification tasks
 - Outlier detection
- Application DEMO--House price prediction

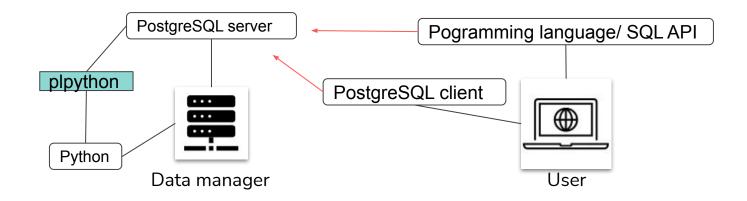
Introduction

Our goal

We want to solve the problem for those who want to:

- 1. easily get a complete table
- 2. quickly find **important variables**
- 3. find and exclude abnormal instances
- 4. **reduce I/O** of data when accessing a remote server
- 5. **get rid of** dealing with **categorical and numerical** variables

Our implemtation framework



Missing values filling

Missing values

	crim	zn	indus	chas	nox	rm	age	dis	rad	tax	ptratio	b	Istat	price
20	NaN	55.0	3.78	None	0.484	6.696	NaN	5.7321	5.0	370.0	17.6	396.90	7.18	23.9
21	37.66190	0.0	18.10	False	0.679	6.202	78.7	1.8629	24.0	666.0	20.2	18.82	14.52	10.9
22	NaN	0.0	13.92	False	NaN	6.009	NaN	5.5027	4.0	289.0	16.0	396.90	10.40	21.7
23	0.22438	0.0	9.69	False	0.585	6.027	79.7	2.4982	6.0	391.0	19.2	396.90	14.33	16.8
24	5.66998	0.0	18.10	True	0.631	6.683	96.8	1.3567	24.0	666.0	20.2	375.33	3.73	50.0
25	0.04819	80.0	3.64	False	0.392	6.108	32.0	9.2203	1.0	315.0	16.4	392.89	6.57	21.9
26	1.42502	NaN	19.58	False	0.871	NaN	100.0	1.7659	5.0	403.0	NaN	364.31	7.39	23.3
27	0.06888	0.0	2.46	False	0.488	6.144	62.2	2.5979	3.0	193.0	17.8	396.90	9.45	36.2
28	0.06162	0.0	4.39	False	0.442	5.898	52.3	8.0136	3.0	352.0	18.8	364.61	12.67	17.2
29	11.08740	0.0	18.10	False	0.718	6.411	100.0	1.8589	24.0	666.0	20.2	318.75	15.02	16.7
		ca	teao	rical	+	nur	nerio	cal	?	D	on't ۱	worry	/!	

Alogorithm

Use information from other attributes to predict the missing values.

	crim	zn	indus	chas	nox	rm	age	dis	rad	tax	ptratio	b	Istat	price
20	NaN	55.0	3.78	None	0.484	6.696	NaN	5.7321	5.0	370.0	17.6	396.90	7.18	23.9
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26	1.42502	NaN	19.58	False	0.871	NaN	100.0	1.7659	5.0	403.0	NaN	364.31	7.39	23.3
27	0.06888	0.0	2.46	False	0.488	6.144	62.2	2.5979	3.0	193.0	17.8	396.90	9.45	36.2
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29	11.08740	0.0	18.10	False	0.718	6.411	100.0	1.8589	24.0	666.0	20.2	318.75	15.02	16.7
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underlying model: histogram-based gradient boosting

Use a regression model to predict

Use a classification model to predict

Usage

	crim	zn	indus	chas	nox	rm	age	dis	rad	tax	ptratio	b	Istat	price
20	NaN	55.0	3.78	None	0.484	6.696	NaN	5.7321	5.0	370.0	17.6	396.90	7.18	23.9
21	37.66190	0.0	18.10	False	0.679	6.202	78.7	1.8629	24.0	666.0	20.2	18.82	14.52	10.9
22	NaN	0.0	13.92	False	NaN	6.009	NaN	5.5027	4.0	289.0	16.0	396.90	10.40	21.7
23	0.22438	0.0	9.69	False	0.585	6.027	79.7	2.4982	6.0	391.0	19.2	396.90	14.33	16.8
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25	0.04819	80.0	3.64	False	0.392	6.108	32.0	9.2203	1.0	315.0	16.4	392.89	6.57	21.9
26	1.42502	NaN	19.58	False	0.871	NaN	100.0	1.7659	5.0	403.0	NaN	364.31	7.39	23.3
27	0.06888	0.0	2.46	False	0.488	6.144	62.2	2.5979	3.0	193.0	17.8	396.90	9.45	36.2
28	0.06162	0.0	4.39	False	0.442	5.898	52.3	8.0136	3.0	352.0	18.8	364.61	12.67	17.2
29	11.08740	0.0	18.10	False	0.718	6.411	100.0	1.8589	24.0	666.0	20.2	318.75	15.02	16.7

	crim	zn	indus	chas	nox	rm	age	dis	rad	tax	ptratio	b	Istat	price
20	0.069066	55.000000	3.78	False	0.484000	6.696000	54.031289	5.7321	5.0	370.0	17.600000	396.90	7.18	23.9
21	37.661900	0.000000	18.10	False	0.679000	6.202000	78.700000	1.8629	24.0	666.0	20.200000	18.82	14.52	10.9
22	-0.363259	0.000000	13.92	False	0.484053	6.009000	53.844987	5.5027	4.0	289.0	16.000000	396.90	10.40	21.7
23	0.224380	0.000000	9.69	False	0.585000	6.027000	79.700000	2.4982	6.0	391.0	19.200000	396.90	14.33	16.8
24	5.669980	0.000000	18.10	True	0.631000	6.683000	96.800000	1.3567	24.0	666.0	20.200000	375.33	3.73	50.0
25	0.048190	80.000000	3.64	False	0.392000	6.108000	32.000000	9.2203	1.0	315.0	16.400000	392.89	6.57	21.9
26	1.425020	-1.150642	19.58	False	0.871000	6.256387	100.000000	1.7659	5.0	403.0	14.566458	364.31	7.39	23.3
27	0.068880	0.000000	2.46	False	0.488000	6.144000	62.200000	2.5979	3.0	193.0	17.800000	396.90	9.45	36.2
28	0.061620	0.000000	4.39	False	0.442000	5.898000	52.300000	8.0136	3.0	352.0	18.800000	364.61	12.67	17.2
29	11.087400	0.000000	18.10	False	0.718000	6.411000	100.000000	1.8589	24.0	666.0	20.200000	318.75	15.02	16.7



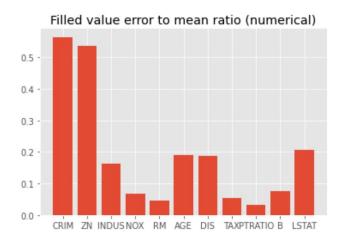
SELECT fill_missing('boston_miss', 'boston_miss_filled', 'price');

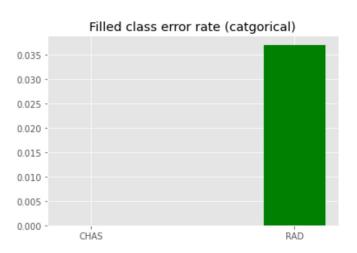
input table

output table

target column (optional)

Performance





Feature Selection

Methods

- Filter based
 - SelectKBest
 - SelectPercentile
- Wrapper-based
 - o RFE
- Embedded
 - SelectFromModel

SelectKbest

SelectPercentile

RFE

SelectFromModel

Result

Outlier Detection

CREATE OR REPLACE FUNCTION OutlierDetection (table_name varchar(63),

method varchar(63) default 'OCSVM',

target varchar(63) default 'NULL')

RETURNS SETOF INT

AS \$\$

Parameters

Table_name: Table name

Method:

OneClassSVM/ Isolation Forest/ Minimum Covariance Determinant/ DBSCAN

Target: column name of target variable, would not be used used to detect outliers

select OutlierDetection('Boston', 'DBSCAN', 'PRICE');

4	outlierdetection integer	<u></u>
1		17
2		65
3		105
4		115
5		117
6		118
7		125
8		126
9		177
10		246

```
--add unique row_idx
```

alter table Boston add unique_id serial;

```
select * from Boston
where unique_id not in ((select OutlierDetection('Boston', 'OCSVM')));
```

Demo

Video Download Link

https://drive.google.com/file/d/16cj54VMcMqK
j1tVexFC0ke-E2LDj_trE/view?usp=sharing