Data Manipulation with Python

Main concepts

☐ File management – The table below summarizes the useful commands to make sure the working directory is correctly set:

Category	Action	Command	
	Change directory to another path	os.chdir(path)	
Paths	Get current working directory	os.getcwd()	
	Join paths	os.path.join(path_1,, path_n)	
	List files and folders in a directory	os.listdir(path)	
Files	Check if path is a file / folder	os.path.isfile(path)	
riles	Check if patif is a file / folder	os.path.isdir(path)	
	Read / write csv file	pd.read_csv(path_to_csv_file)	
	nead / write csv me	df.to_csv(path_to_csv_file)	

 $\hfill\Box$ Chaining – It is common to have successive methods applied to a data frame to improve readability and make the processing steps more concise. The method chaining is done as follows:

```
# df gets some_operation_1, then some_operation_2, ..., then some_operation_n (df .some_operation_2(params_1) .some_operation_2(params_2) ... .some_operation_n(params_n))
```

 $\hfill\Box$ Exploring the data — The table below summarizes the main functions used to get a complete overview of the data:

Category	Action	Command
	Select columns of interest	df[col_list]
Look at data	Remove unwanted columns	df.drop(col_list,axis=1)
	Look at <i>n</i> first rows / last rows	df.head(n) / df.tail(n)
	Summary statistics of columns	df.describe()
Paths	Data types of columns	df.dtypes / df.info()
ratiis	Number of (rows, columns)	df.shape

 $\hfill\square$ Data types — The table below sums up the main data types that can be contained in columns:

	Data type	Description	Example
	object	String-related data	'teddy bear'
	float64	Numerical data	24.0
Data prepr	int64	Numeric data that are integer	24
☐ Filtering	datetime64	vsTancestangs some conditions as fol	'2020-01-01 00:01:00'

Python

df[df['some_col'] some_operation some_value_or_list_or_col]

where some operation is one of the following:

Category	Operation	Command
	Equality / non-equality	== / !=
Basic	Inequalities	<, <=, >=, >
	And / or	&/
	Check for missing value	pd.isnull()
Advanced	Belonging	.isin([val_1,, val_n])
	Pattern matching	.str.contains('val')

☐ Changing columns – The table below summarizes the main columnoperations:

Operation	Command
Add new columns on top of old ones	<pre>df.assign(new_col=lambdax:some_operation(x))</pre>
Rename columns	<pre>df.rename(columns={ current_col':'new_col_name'}) })</pre>
Unite columns	<pre>df['new_merged_col']=(df[old_cols_list].agg('-</pre>

☐ Conditional column — A column can take different values with respect to a particular set of conditions with the np.select() command asfollows:

```
Python

np.select(
  [condition_1, ..., condition_n], # If condition_1 condition_n [value_1, ..., value_n],
  default=default_value # Otherwise, default_value
)
```

Remark: the np. where (condition if true, value_true, value_other) command can be used and is easier to manipulate if there is only one condition.

 $\hfill\Box$ Mathematical operations – The table below sums up the main mathematical operations that can be performed on columns:

Operation	Command	
$\sqrt{\overline{x}}$	np.sqrt(x)	
x∫	np.floor(x)	
x	np.ceil(x)	

□ **Datetime conversion** − Fields containing datetime values are converted from string to date- time as follows:

```
pd.to_datetime(col, format)
```

where format is a string describing the structure of the field and using the commands summarized in the table below:

Category	Command	Description	Example
Year	′%Y′ / ′%y′	With / without century	2020 / 20
Month	'%B' / '%b' / '%m'	Full / abbreviated / numerical	August / Aug/ 8
Weekday	'%A' / '%a'	Full / abbreviated	Sunday / Sun
Weekday	'%u' / '%w'	Number (1-7) / Number (0-6)	7/0
Day	'%d' / '%j'	Of the month / of the year	09 / 222
Time	'%H' / '%M'	Hour / minute	09 / 40
Timezone	′%Z′ / ′%z′	String / Number of hours from UTC	EST / -0400

 \square Date properties – In order to extract a date-related property from a datetime object, the following command is used:

```
Python

datetime_object.strftime(format)
```

where format follows the same convention as in the table above.

Data frame transformation

☐ **Merging data frames** – We can merge two data frames by a given field asfollows:

```
df1.merge(df2, join_field, join_type)
```

where join field indicates fields where the join needs to happen:

Case	Fields are equal	Fields are different	
Command	on='field'	left_on='field_1',right_on='field_2'	

and where join_type indicates the join type, and is one of the following:

Join type	Option	Illustration		
Inner join	how='inner'	df_1 df_2		
Left join	how='left'	df_1		
Right join	how='right'	df_1		
Full join	how='outer'	df_1 df_2		

Remark: a cross join can be done by joining on an undifferentiated column, typically done by creating a temporary column equal to 1.

□ Concatenation – The table below summarizes the different ways data frames can be con- catenated:

Туре	Command	Illustration	
Rows	pd.concat([df_1,, df_n],axis=0)	df_1 df_2 : df_n	
Columns	pd.concat([df_1,, df_n],axis=1)	df_1 df_2 df_n	

☐ Common transformations — The common data frame transformations are summarized in the table below:

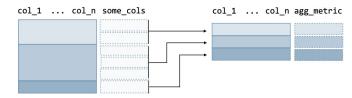
Туре	Command	Illustration		
,		Before	After	
Long to wide	pd.pivot table(df,values='value', index=some cols, columns='key', aggfunc=np.sum)	key_1	some_cols key_1 key_n	
Wide to long	pd.melt(df,var_name='key', value_name='value', value_vars= 'key_1',,'key_n'],id_vars=some_cols	some_cols key_1 key_n	some_cols key_value	

☐ **Row operations** – The following actions are used to make operations on rows of the data frame:

Action	Command	Illustration	
		Before	After
Sort with respect to columns	<pre>df.sort_values(by=['col_1',,'col_n'], ascending=True)</pre>	col_1 col_2 col_3 other_cols	col_1 col_2 col_3 other_cols
Dropping duplicates	df.drop_duplicates()	col_1 col_2 col_3 col_4 col_5	col_1 col_2 col_3 col_4 col_5
Drop rows with at least a null value	df.dropna()	col_1 col_2 col_3 col_4 col_5	col_1 col_2 col_3 col_4 col_5

Aggregations

☐ **Grouping data** – A data frame can be aggregated with respect to given columns as follows:



The Python command is as follows:

```
Python
(df
.groupby(['col_1', ...,'col_n'])
.agg({'col': builtin_agg})
```

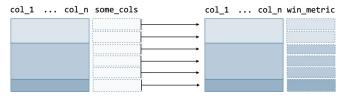
where builtin_agg is among the following:

Category	Action	Command
Properties	Count of observations 'count'	
	Sum of values of observations	'sum'
Values	Max / min of values of observations	'max' / 'min'
	Mean / median of values of observations	'mean' / 'median'
	Standard deviation / variance across observations	'std' / 'var'

☐ Custom aggregations— It is possible to perform customized aggregations by using lambda functions as follows:

Window functions

☐ **Definition** – A window function computes a metric over groups and has the following structure:



The Python command is as follows:

```
(df .assign(win_metric=lambdax: x.groupby(['col_1', ...,'col_n'])['col'].window_function(params))
```

Remark: applying a window function will not change the initial number of rows of the data frame.

☐ Row numbering — The table below summarizes the main commands that rank each row across specified groups, ordered by a specific field:

Join type	Command	Example
x.rank(method='first')	Ties are given different ranks	1, 2, 3, 4
x.rank(method='min')	Ties are given same rank and skip numbers	1, 2.5, 2.5, 4
x.rank(method='dense')	Ties are given same rank and do not skip numbers	1, 2, 2, 3

□ Values – The following window functions allow to keep track of specific types of values with respect to the group:

Command	Description
x.shift(n)	Takes the $n^{ m th}$ previous value of the column
x.shift(-n)	Takes the $n^{ m th}$ following value of the column