FUNDAMENTOS E TÉCNICAS EM CIÊNCIAS DE DADOS

PROF. JOSENALDE OLIVEIRA

josenalde@eaj.ufrn.br https://github.com/josenalde/datascience

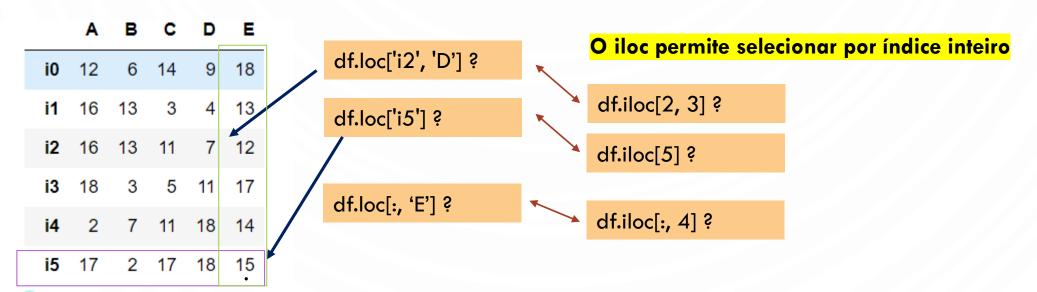
ANÁLISE E DESENVOLVIMENTO DE SISTEMAS - UFRN

PANDAS #2 — EXPLORANDO DATAFRAMES

- SELECIONAR COLUNAS, LINHAS, ITENS INDIVIDUAIS COM LOCALIZAÇÃO DE ÍNDICES
- MÉTODOS PANDAS PARA PRODUZIR ARRAYS BOOLEANOS
- OPERADORES BOOLEANOS COMBINADAS PARA REALIZAR OPERAÇÕES MAIS COMPLEXAS
- AGREGAÇÃO PARA ANÁLISE MAIS AVANÇADA COM LOOPS

```
d = np.random.randint(2,20, size=(30,5))
listIndex = []
for i in range(0,30):
    listIndex.append('i' + str(i))

df = pd.DataFrame(data=d, columns=list('ABCDE'), index=listIndex)
```



PANDAS #2 – EXPLORANDO DATAFRAMES

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	df	iloc.	[1:3]	
	A	В	С	D	E
i0	12	6	14	9	18
i1	16	13	3	4	13
i2	16	13	11	7	12
i3	18	3	5	11	17
i4	2	7	11	18	14
i5	17	2	17	18	15

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	df	f.iloc	[1:3]	
	Α	В	С	D	E
i0	12	6	14	9	18
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i2	16	13	11	7	12
i3	18	3	5	11	17
i4	2	7	11	18	14
i5	17	2	17	18	15

	dt	Jocl		13]	
	Α	В	С	D	E
i0	12	6	14	9	18
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i2	16	13	11	7	12
i3	18	3	5	11	17
i4	2	7	11	18	14
i5	17	2	17	18	15

PANDAS #2 – MÁSCARAS BOOLEANAS

Seja o dataset FORTUNE1000.csv

df2 = pd.read_csv('../datasets/fortune1000.csv')

ra	nk	title	Previous Rank	Revenues (\$M)	Revenue Change	Profits (\$M)	Profit Change	Assets (\$M)	Value as of 3/29/18 (\$M)	Employees	CEO	CEO Title	Sector	Industry	Years on Fortune 500 List	City	State	Latitude	Longitude
0	1	Walmart	1	\$500,343	3.00%	\$9,862.00	-27.70%	\$204,522	\$263,563	2,300,000	C. Douglas McMillon	President, Chief Executive Officer & Director	Retailing	General Merchandisers	24	Bentonville	AR	36.372854	-94.208817
1	2	Exxon Mobil	4	\$244,363	17.40%	\$19,710.00	151.40%	\$348,691	\$316,157	71,200	Darren W. Woods	Chairman & Chief Executive Officer	Energy	Petroleum Refining	24	Irving	TX	32.814018	-96.948894
2	3	Berkshire Hathaway	2	\$242,137	8.30%	\$44,940.00	86.70%	\$702,095	\$492,008	377,000	Warren E. Buffett	Chairman, President & Chief Executive Officer	Financials	Insurance: Property and Casualty (Stock)	24	Omaha	NE	41.256537	-95.934503
3	4	Apple	3	\$229,234	6.30%	\$48,351.00	5.80%	\$375,319	\$851,318	123,000	Timothy D. Cook	Chairman & Chief Executive Officer	Technology	Computers, Office Equipment	24	Cupertino	CA	37.322998	-122.032182
4	5	UnitedHealth Group	6	\$201,159	8.80%	\$10,558.00	50.50%	\$139,058	\$207,080	260,000	David S. Wichmann	Chairman & Chief Executive Officer	Health Care	Health Care: Insurance and Managed Care	24	Minnetonka	MN	44.921184	-93.468749
	ra 00 11	1 2 2 3	1 2 Exxon Mobil 2 3 Berkshire Hathaway 3 4 Apple	rank title Rank 0 1 Walmart 1 1 2 Exxon Mobil 4 2 3 Berkshire Hathaway 2 3 4 Apple 3 4 5 UnitedHealth 6	rank title Rank (\$M) 0 1 Walmart 1 \$500,343 1 2 Exxon Mobil 4 \$244,363 2 3 Berkshire Hathaway 2 \$242,137 3 4 Apple 3 \$229,234 4 5 UnitedHealth 6 \$201,159	rank title Rank (\$M) Change 0 1 Walmart 1 \$500,343 3.00% 1 2 Exxon Mobil 4 \$244,363 17.40% 2 3 Berkshire Hathaway 2 \$242,137 8.30% 3 4 Apple 3 \$229,234 6.30% 4 5 UnitedHealth 6 \$201,159 8.80%	rank title Rank (\$M) Change (\$M) 0 1 Walmart 1 \$500,343 3.00% \$9,862.00 1 2 Exxon Mobil 4 \$244,363 17.40% \$19,710.00 2 3 Berkshire Hathaway 2 \$242,137 8.30% \$44,940.00 3 4 Apple 3 \$229,234 6.30% \$48,351.00 4 5 UnitedHealth 6 \$201,159 8,80% \$10,558.00	Tank title Rank (\$M) Change (\$M) Change 0 1 Walmart 1 \$500,343 3.00% \$9,862.00 -27.70% 1 2 Exxon Mobil 4 \$244,363 17.40% \$19,710.00 151.40% 2 3 Berkshire Hathaway 2 \$242,137 8.30% \$44,940.00 86.70% 3 4 Apple 3 \$229,234 6.30% \$48,351.00 5.80% 4 5 UnitedHealth 6 \$201,159 8.80% \$10,558.00 50,50%	Tank title Rank (\$M) Change (\$M) Change (\$M) 1 Walmart 1 \$500,343 3.00% \$9,862.00 -27.70% \$204,522 1 2 Exxon Mobil 4 \$244,363 17.40% \$19,710.00 151.40% \$348,691 2 3 Berkshire Hathaway 2 \$242,137 8.30% \$44,940.00 86.70% \$702,095 3 4 Apple 3 \$229,234 6.30% \$48,351.00 5.80% \$375,319	rank title Previous Rank Revenue (\$M) Profit (\$M) Profit (\$M) Assets (\$M) of 3/29/18 (\$M) 0 1 Walmart 1 \$500,343 3.00% \$9,862.00 -27.70% \$204,522 \$263,563 1 2 Exxon Mobil 4 \$244,363 17.40% \$19,710.00 151.40% \$348,691 \$316,157 2 3 Berkshire Hathaway 2 \$242,137 8.30% \$44,940.00 86.70% \$702,095 \$492,008 3 4 Apple 3 \$229,234 6.30% \$48,351.00 5.80% \$375,319 \$851,318 4 5 UnitedHealth 6 \$201,159 8.80% \$10,558.00 50.50% \$139,058 \$207,080	Trank title Previous Revenue (\$M) Change (\$M) Change (\$M) Change of 3/29/18 (\$M) of 3/29/18 (\$M) change of 3/29/18	rank title revenue (\$M) revenue (\$M) rione (\$M) Assets (\$M) Assets (\$M) Employees (\$M) CEO 0 1 Walmart 1 \$500,343 3.00% \$9,862.00 -27.70% \$204,522 \$263,563 2,300,000 Douglas McMillon 1 2 Exxon Mobil 4 \$244,363 17.40% \$19,710.00 151.40% \$348,691 \$316,157 71,200 Darren W. Woods 2 3 Berkshire Hathaway 2 \$242,137 8.30% \$44,940.00 86.70% \$702,095 \$492,008 377,000 Warren E. Buffett 3 4 Apple 3 \$229,234 6.30% \$48,351.00 5.80% \$375,319 \$851,318 123,000 Timothy D. Cook 4 5 UnitedHealth 6 \$201,159 8.90% \$10,599.00 50,50% \$129,059 \$207,090 260,000 David S.	Tank title Tevilots Rank Ra	Tank Tank	title Rank (\$M) Change (\$M) Ch	title Rank (SM) Change (SM) (SM) Change (SM) (SM) Change (SM) Change (SM) Change (SM) Change (SM) (SM) (SM) (SM) (SM) (SM) (SM) (SM)	Tank Tank	Tank Tank	Tank Hittle Previous Rank Hittle Previous Rank Ra

df2.columns

Index(['rank', 'title', 'Previous Rank', 'Revenues (\$M)',
'Revenue Change', 'Profits (\$M)', 'Profit Change', 'Assets (\$M)', 'Mkt Value as of 3/29/18 (\$M)',
'Employees', 'CEO', 'CEO Title', 'Sector', 'Industry', 'Years on Fortune 500 List', 'City', 'State',
'Latitude', 'Longitude'], dtype='object')

PANDAS #2 – MÁSCARAS BOOLEANAS

Index(['rank', 'title', 'Previous Rank', 'Revenues (\$M)',
'Revenue Change', 'Profits (\$M)', 'Profit Change', 'Assets (\$M)', 'Mkt Value as of 3/29/18 (\$M)',
'Employees', 'CEO', 'CEO Title', 'Sector', 'Industry', 'Years on Fortune 500 List', 'City', 'State',
'Latitude', 'Longitude'], dtype='object')

is_computer = df2['Industry'].str.startswith('Computers') #cria a mascara booleana

is_computer

,		J P 0. C C.			ra	ınk	title	Previous Rank	Revenues (\$M)	Revenue Change	Profits (\$M)	Profit Change	Assets (\$M)	of 3/29/18 (\$M)	Employees	CEO	CEO Title	Sector	Industry	F 6
	0 1 2	False False False			0	1	Walmart	1	\$500,343	3.00%	\$9,862.00	-27.70%	\$204,522	\$263,563	2,300,000	C. Douglas McMillon	President, Chief Executive Officer & Director	Retailing	General Merchandisers	
	3 4	True False 			1	2	Exxon Mobil	4	\$244,363	17.40%	\$19,710.00	151.40%	\$348,691	\$316,157	71,200	Darren W. Woods	Chairman & Chief Executive Officer	Energy	Petroleum Refining	
	995 996 997 998	False False False False	,		2	3	Berkshire Hathaway	2	\$242,137	8.30%	\$44,940.00	86.70%	\$702,095	\$492,008	377,000	Warren E. Buffett	Chairman, President & Chief Executive Officer	Financials	Insurance: Property and Casualty (Stock)	
	999	False Industry,	Length:	10(3	4	Apple	3	\$229,234	6.30%	\$48,351.00	5.80%	\$375,319	\$851,318	123,000	Timothy D. Cook	Chairman & Chief Executive Officer	Technology	Computers, Office Equipment	
)				4	5	UnitedHealth Group	6	\$201,159	8.80%	\$10,558.00	50.50%	\$ 139,058	\$207,080	260,000	David S. Wichmann	Chairman & Chief Executive Officer	Health Care	Health Care: Insurance and Managed Care	

cols = ['rank', 'title', 'Profits (\$M)', 'Employees']
df2.loc[is computer, cols] #aplica a máscara nas colunas

PANDAS #2 – MÁSCARAS BOOLEANAS

```
Index(['rank', 'title', 'Previous Rank', 'Revenues ($M)',
'Revenue Change', 'Profits ($M)', 'Profit Change', 'Assets ($M)', 'Mkt Value as of 3/29/18 ($M)',
'Employees', 'CEO', 'CEO Title', 'Sector', 'Industry', 'Years on Fortune 500 List', 'City', 'State',
'Latitude', 'Longitude'], dtype='object')

is computed = df2['Industry'] stp stantswith('Computed 2) tanks a massage basis as
```

is_computer = df2['Industry'].str.startswith('Computers') #cria a mascara booleana
is_computer

cols = ['rank', 'title', 'Profits (\$M)', 'Employees']
df2.loc[is computer, cols] #aplica a máscara nas colunas

	rank	title	Profits (\$M)	Employees
3	4	Apple	\$48,351.00	123,000
34	35	Dell Technologies	(\$3,728.00)	145,000
57	58	HP	\$2,526.00	49,000
106	107	Hewlett Packard Enterprise	\$344.00	66,000
157	158	Western Digital	\$397.00	67,629
290	291	Xerox	\$195.00	36,100
431	432	NCR	\$232.00	34,000
494	495	NetApp	\$509.00	10,100
550	551	Diebold Nixdorf	(\$233.10)	23,000
656	657	Pitney Bowes	\$261.30	14,700
823	824	Super Micro Computer	\$69.30	2,699

```
Coluna Employees com
strings com separadores vírgula
Função de conversão str-float
Defeituosa neste caso! Remover virgulas
```

```
print('-----')
print(df2.dtypes)
# Comparação incorreta, pois o campo Employees é object-string
\#c1 = df2['Employees'] > 300000
df2['Employees'] = df2['Employees'].str.replace(',', '')
print(df2)
print('-----')
df2['Employees'] = df2['Employees'].astype(float)
print(df2.dtypes)
                                                   title Sector Employees
                                        rank
c1 = df2['Employees'] > 70000
c2 = df2['Sector'] == 'Energy'
                                          2 Exxon Mobil Energy
                                                                71200.0
cond = c1 & c2 #máscara
cols = ['rank', 'title', 'Sector', 'Employees']
df2.loc[cond, cols]
```

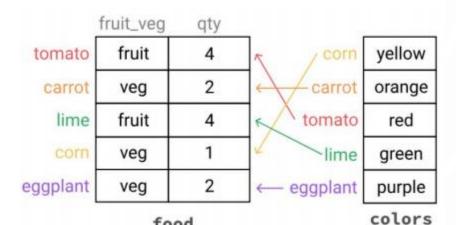
PANDAS #2 – ALINHAMENTO DE ÍNDICES

Criar dataframes e comandos que reproduzam este exemplo:

1	ruit_veg	qty
tomato	fruit	4
carrot	veg	2
lime	fruit	4
corn	veg	1
eggplant	veg	2
5	fo	od

55	
com	yellow
carrot	orange
tomato	red
lime	green
eggplant	purple
	colors

	fruit_veg	qty	color
tomato	fruit	4	red
carrot	veg	2	orange
lime	fruit	4	green
corn	veg	1	yellow
eggplant	veg	2	purple



food

food["color"] = colors

food

https://pandas.pydata.org/docs/reference/api/pandas.concat.html?highlight=concat

PANDAS #2 – PARA IR ALÉM

Estudar o notebook de exemplo com análise dos commits do Kernel Linux ao longo da história

<u>Exploring-the-evolution-of-Linux-Datacamp-Project/notebook.ipynb at master · vneogi199/Exploring-the-evolution-of-Linux-Datacamp-Project · GitHub</u>