

Lesson 3: Your First Spark Application

3.5 Making Sense of Data: Summary Statistics and Distributions

Frequently Occurring Values

- `dataframe.freqItems(columns, support)`

Note: this is an approximate algorithm that **always** returns all the frequent items, but may contain false positives.

required minimum
proportion of rows

```
freq_items = df.freqItems(['school_city', 'primary_focus_area', \
                           'grade_level', 'poverty_level', 'resource'], 0.7).collect()
```

```
freq_items[0]
```

```
Row(school_city_freqItems=[u'Los Angeles'], primary_focus_area_freqItems=[u'Literacy & Language'], grade_level_freqItems=[u'Grades PreK-2'], poverty_level_freqItems=[u'highest poverty'], resource_freqItems=[u'Supplies'])
```

<http://dl.acm.org/citation.cfm?doid=762471.762473>



Summary Statistics

- `dataframe.describe(column_name)`

```
df.select('total_donations', 'num_donors', 'students_reached', \
         df_dates['total_price_excluding_optional_support'].alias('p_exclude'), \
         df_dates['total_price_including_optional_support'].alias('p_include')) \
     .describe().show()
```

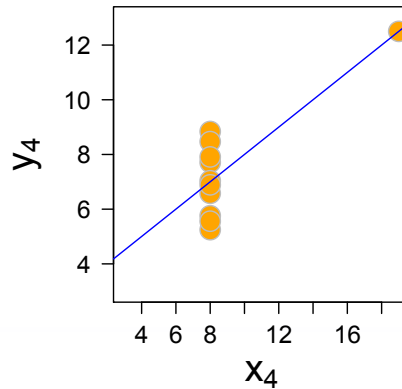
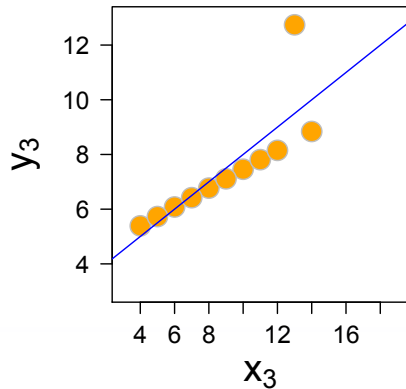
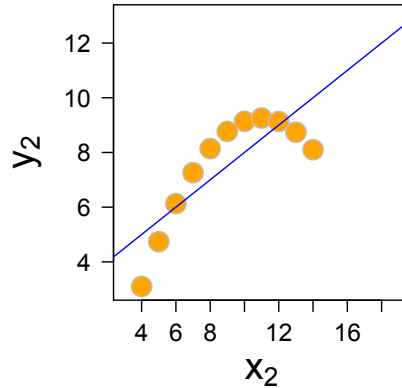
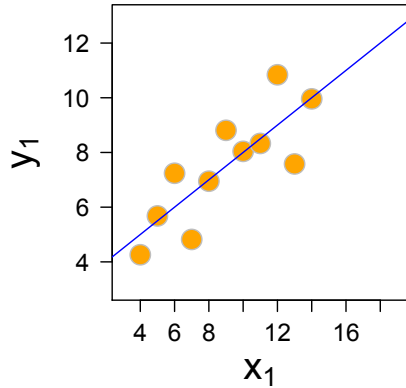
summary	total_donations	num_donors	students_reached	p_exclude	p_include
count	771929	771929	771779	771929	771929
mean	370.85023398481707	4.264279486843997	96.71620114048193	569.6223687446723	676.180708551764
stddev	733.4647726421459	6.132976060232441	2118.592960253374	11763.955807309705	14344.347534777195
min	0.0	0.0	0.0	0.0	0.0
max	244778.0	521.0	999999.0	1.0250017E7	1.2500021E7



Interlude: Sometimes numbers aren't enough!



Anscombe's Quartet



Mean (x)	9
Sample Variance (x)	11
Mean (y)	7.50
Sample Variance (y)	4.127
Correlation	0.816
Linear Regression	$y = 3.00 + 0.500x$



Distributions

RDD

- `rdd.histogram()`
- `rdd.stats()`

DataFrame

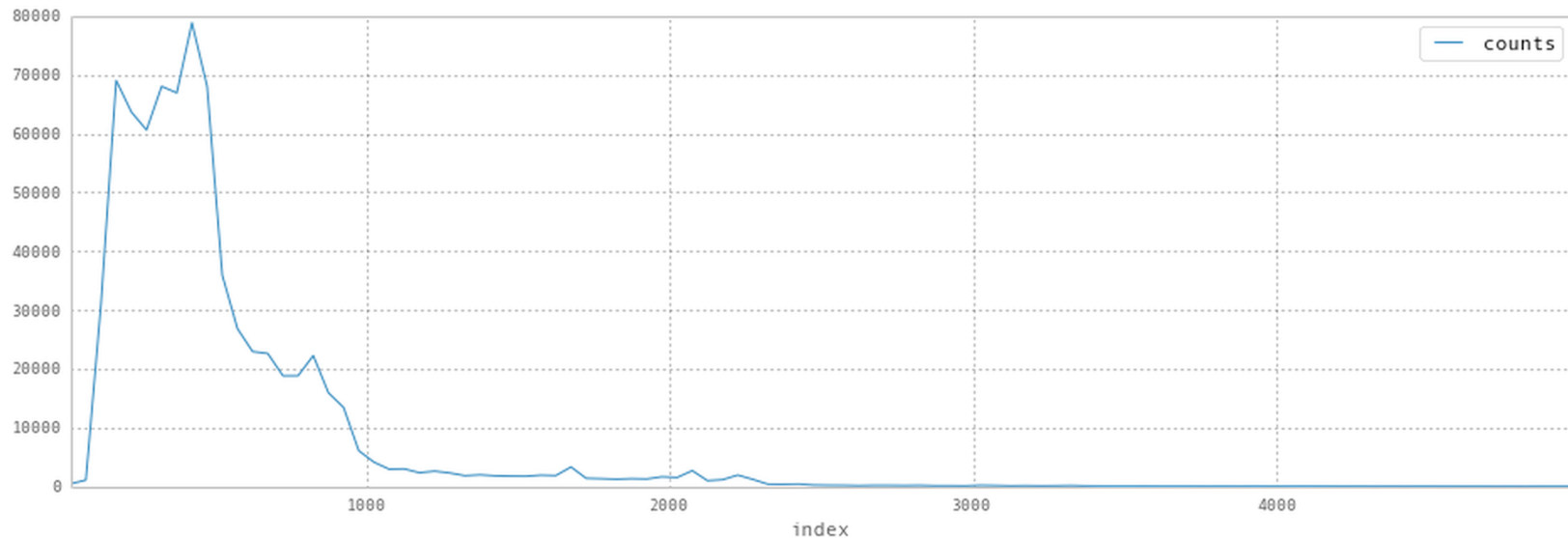
- `dataframe.groupby('column_name').count()`
- `dataframe.describe('column_name')`



```
price_rdd = df_no_null.select('total_price_excluding_optional_support').rdd.map(lambda r: r.asDict().values()[0])
```

```
def plot_rdd_hist(hist):  
    idx = []  
  
    for i in range(len(hist[0]) - 1):  
        idx.append((hist[0][i] + hist[0][i+1]) / 2)  
  
    pd.DataFrame({'counts': hist[1], 'index': idx}).set_index('index').plot(figsize=(16,5))
```

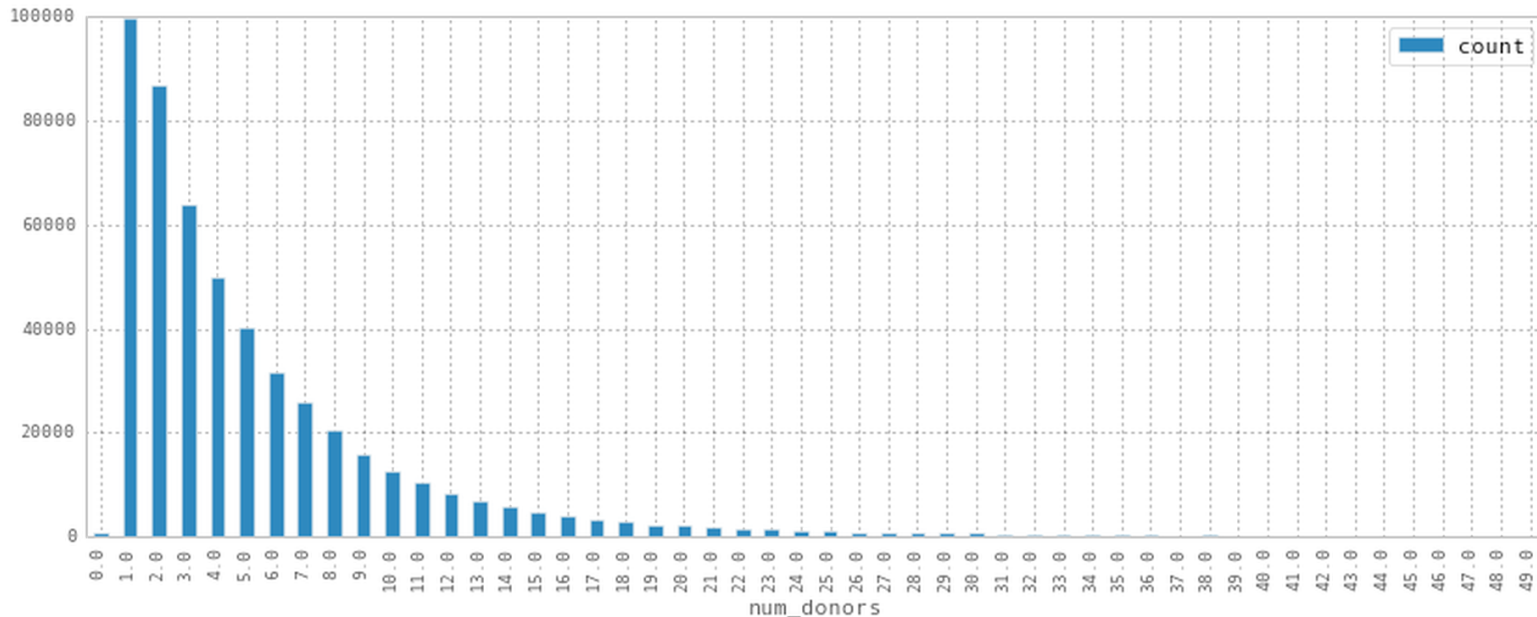
```
plot_rdd_hist(price_rdd.filter(lambda x: x < 5000).histogram(100))
```



```
def spark_histogram(df, column):  
    donor_counts = df.groupby(column).count()  
    donor_df = donor_counts.toPandas()  
    donor_df[column] = donor_df.num_donors.astype(float)  
    return donor_df.sort(column).set_index(column).iloc[:50,:].plot(kind='bar', figsize=(14,5))
```

```
spark_histogram(df_complete, 'num_donors')
```

<matplotlib.axes._subplots.AxesSubplot at 0x113b2be50>



Interactions

- `dataframe.crosstab()`
- `dataframe.corr()`

```
df_no_null.stat.corr('total_price_excluding_optional_support', 'num_donors')
```

```
0.007004254706419042
```

```
df_no_null.stat.corr('total_price_excluding_optional_support', 'students_reached')
```

```
0.0006159991686679948
```

```
df_no_null.stat.corr('total_price_excluding_optional_support', 'total_price_including_optional_support')
```

```
0.9999972199123168
```



```
df_dates.crosstab('resource_type', 'funding_status').show()
df_dates.crosstab('primary_focus_area', 'resource_type').show()
```

resource_type_funding_status	live	completed	reallocated	expired
null	2	28	0	18
Other	4542	54610	747	22550
Books	5982	118810	1527	34554
Visitors	102	806	6	341
Supplies	11939	185870	2602	63406
Trips	347	4381	62	1474
Technology	18957	150500	2256	85510

primary_focus_area_resource_type	Trips	Visitors	Other	Technology	Books	Supplies	null
Literacy & Language	630	228	32795	109605	127282	75924	4
null	0	0	0	0	1	0	41
Applied Learning	1197	104	9429	17869	4863	22596	0
Math & Science	1902	323	16353	75189	11746	89101	3
Music & The Arts	947	441	8305	19289	2883	37804	0
Health & Sports	159	54	4633	3054	432	12970	0
Special Needs	241	32	7636	19359	4112	17151	0
History & Civics	1188	73	3298	12858	9554	8271	0



Review

- Interactive REPL
- Rapid computation (especially aggregates) on large amounts of data
- High level abstractions for efficient querying of data
- “Condense” data for easier local exploration and visualization

