U.S. Workplace Injury Analysis





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# **Project Overview**



Within this project we will analyze data of work-related injuries and illnesses from different employers in United States.

The objective is to explore the officially reported data from **OSHA** to have insights that can serve to **spread awareness and contribute to improve workplace health & safety**, and eventually save people lives.





Companies may also take these insights into consideration to:

- ✓ see relative level of injuries and illnesses among different industries
- ✓ understand why employees are suffering from injuries (which sometimes cause fatalities)
- ✓ determine problem areas and progress in preventing work-related injuries and illnesses

### Data source



Data is extracted from OSHA (Occupational Safety and Health Administration), which is the federal agency of the United States, part of the United States Department of Labor, that regulates workplace safety and health: https://www.osha.gov/Establishment-Specific-Injury-and-Illness-Data



### **Incident Rate**



As per US Bureau of Labor Statistics, an incidence rate of injuries and illnesses is computed from the following formula:

$$TCR = \frac{(Number\ of\ injuries\ and\ illness)\ x\ 200,000}{Employee\ hours\ worked}$$

$$DART = \frac{(Number\ of\ injuries\ and\ illnesses\ with\ days\ away\ from\ work,\ job\ transfer,\ or\ restriction)\ x\ 200,000}{Employee\ hours\ worked}$$

#### **Notes:**

- The 200,000 hours in the formula represents the equivalent of 100 employees working 40 hours per week, 50 weeks
  per year, and provides the standard base for the incidence rates).
- Hours worked should not include any nonwork time, even though paid, such as vacation, sick leave, holidays, etc.

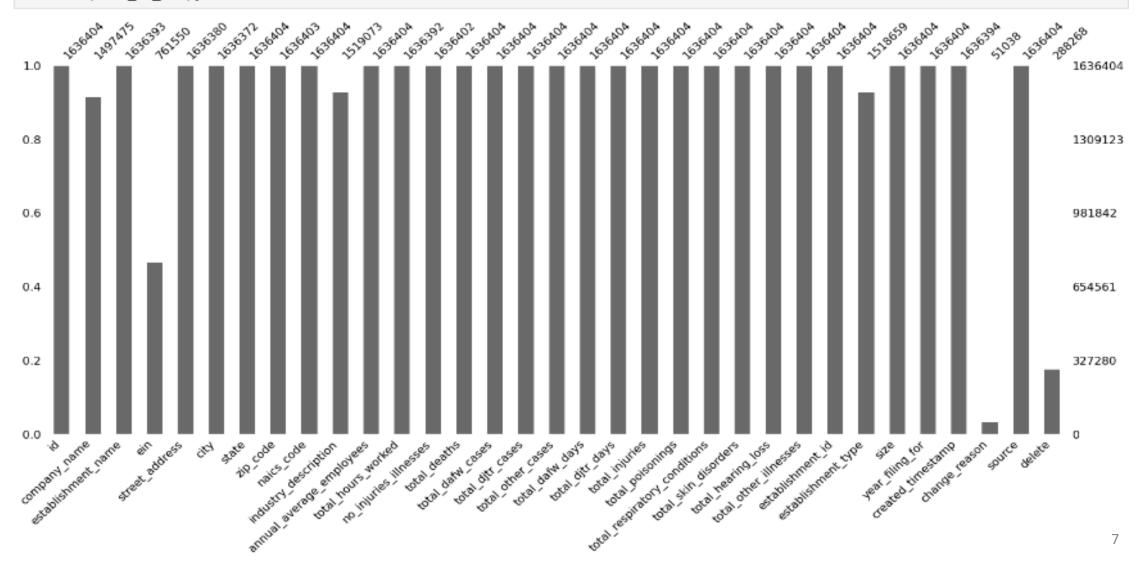


Original Dataframe size: Number of rows = 1636404; Number of Columns = 33

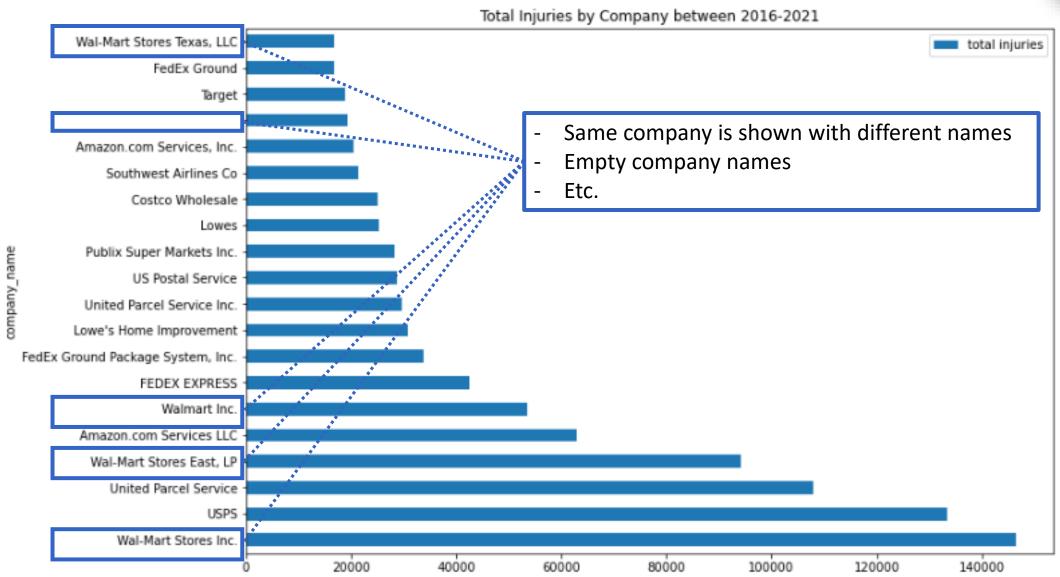
	id	company_name	establishment_name	ein	street_address	city	state	zip_code	naics_code	industry_description	annual_average_employees	total_hours_worked	ī
0	4.0	McKamish, Inc.	McKamish, Inc.	NaN	50 55th Street	Pittsburgh	PA	15201.0	238220.0	Heating, ventilation and air-conditioning (HVA	280.0	579688.0	
1	5.0	The Talaria Company, LLC	The Hinckley Company	NaN	40 Industrial Way	Trenton	ME	4605.0	336612.0	Pleasure boats manufacturing	246.0	501578.0	
2	6.0	Williamsburg Manufacturing	Williamsburg Manufacturing	NaN	408 Maplewood Ave	Williamsburg	IA	52361.0	336370.0	Motor vehicle metal parts stamping	273.0	619945.0	
3	7.0	The Talaria Company, LLC	Morris Yachts, LLC	NaN	27 Ramp Road	Trenton	ME	4605.0	336612.0	Pleasure boats manufacturing	33.0	75794.0	
4	8.0	The Talaria Company, LLC	Hunt Yachts, LLC	NaN	1909 Alden Landing	Portsmouth	RI	2871.0	336612.0	Pleasure boats manufacturing	43.0	114734.0	
4												<b>•</b>	



# visual plot of null values per column to see density of dataframe
msno.bar(osha\_df\_raw);





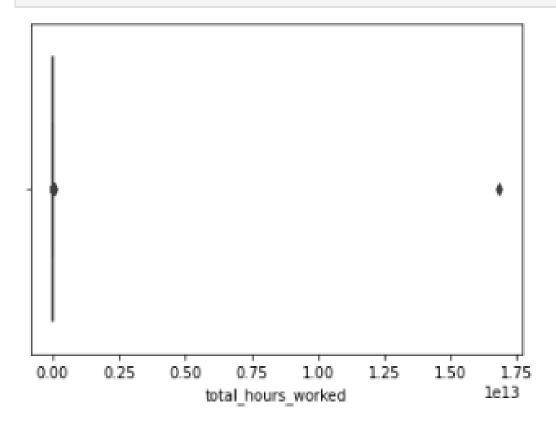


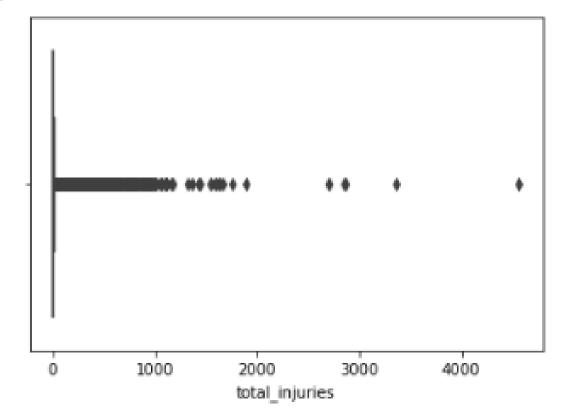


#### **Outlier values**

# box plot to see distribution of total\_hours\_worked
sns.boxplot(x="total\_hours\_worked", data=osha\_df\_raw);

# box plot to see distribution of total\_injuries
sns.boxplot(x="total\_injuries", data=osha\_df\_raw);





# **Data Processing**



In any data science project, data wrangling is a very important step, since it removes the risk by ensuring data is in a reliable state before it is analyzed and leveraged, making it to be a critical part of the analytical process. Thus, despite dataset quality is good, it is highly advised to process and format the data.

- ✓ Clean the data: by keeping only the columns that are meaningful for the analysis; and use statistics to detect and remove outliers with reference to its interquartile range.
- ✓ Format the data, such as data conversion, remove negative numeric values, filling empty values, removing special characters, standardize company name, etc.



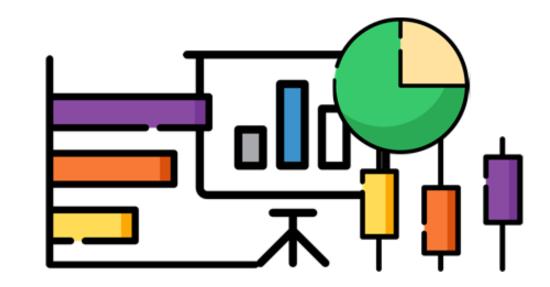
# **Exploratory Data Analysis**



After processing the raw data, we will use the clean dataset output to perform EDA (Exploratory Data Analysis), to plot our variables in order to extract meaningful insights and conclusions about our data, by means of visual explorations.

EDA is based on graphical and descriptive techniques whose objective is to:

- ✓ gain intuition about the data
- ✓ detect outliers
- ✓ extract important variables
- ✓ discover underlying structures in the data
- ✓ It also allows organizing the data, detecting failures and evaluating the existence of missing data



# Technology Stack



- Python (Jupyter)
- Web Scrapping / Requests / BeautifulSoùp
- Numpy, Pandas, Pickle
- Data wrangling. Main functions:
  - import\_data(), combine\_csv()
  - df\_clean\_format(\*\*kwargs parameters)
- **DA** and descriptive statistics techniques
- Matplotlib, Seaborn
- PowerBi
- **※** ..

































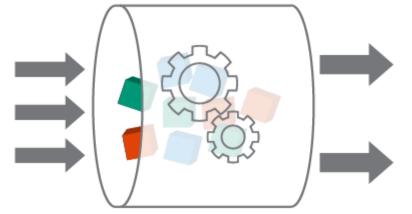


#### Input

osha\_df\_raw.isnull().sum()

id	9
company_name	138929
establishment_name	11
ein	874854
street_address	24
city	32
state	9
zip_code	1
naics_code	9
industry_description	117331
annual_average_employees	9
total_hours_worked	12
no_injuries_illnesses	2
total_deaths	9
total_dafw_cases	9
total_djtr_cases	9
total_other_cases	9
total_dafw_days	9
total_djtr_days	9
total_injuries	9
total_poisonings	9
total_respiratory_conditions	9
total_skin_disorders	9
total_hearing_loss	9
total_other_illnesses	9
establishment_id	9
establishment_type	117745
size	9
year_filing_for	9
created_timestamp	10
change_reason	1585366
source	9
delete	1348136
dtype: int64	

Processing



#### Output

osha_df_raw.isnull().sum()

id	9
company_name	0
establishment_name	10
state	0
naics_code	0
total_hours_worked	6
injury_illness	1
total_deaths	9
total_dafw_cases	0
total_djtr_cases	0
total_other_cases	9
total_dafw_days	0
total_djtr_days	0
total_injuries	9
size	0
year_filing_for	9
naics_industry_description	3216
TCR	0
DART	0
dtype: int64	

Almost no null values!





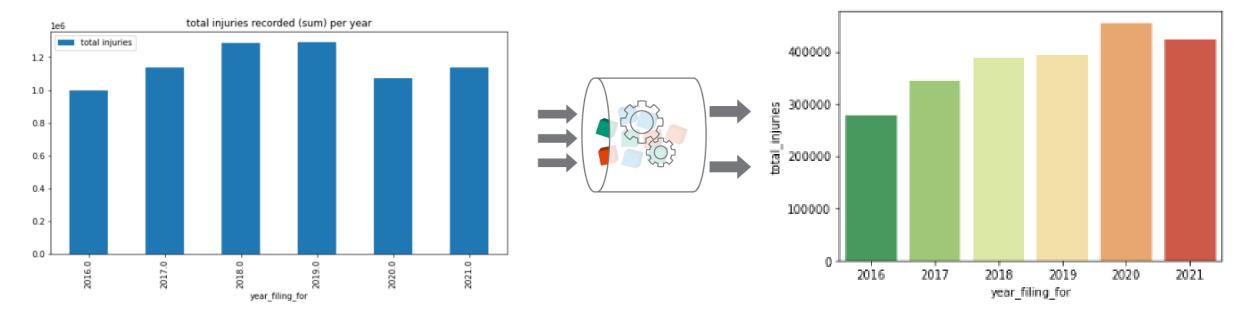
Input Processing Output total\_hours\_worked 100000 1.50 80000 1.25 1.00 60000 0.75 0.50 40000 0.25 20000 0.00 0.0 0.5 1.0 1.5 le13 400000 300000 100000 200000 total hours worked Same histogram plot is now much more meaningful



Input

Processing

Output



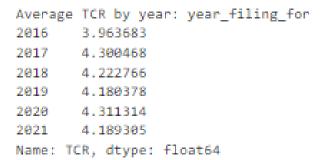


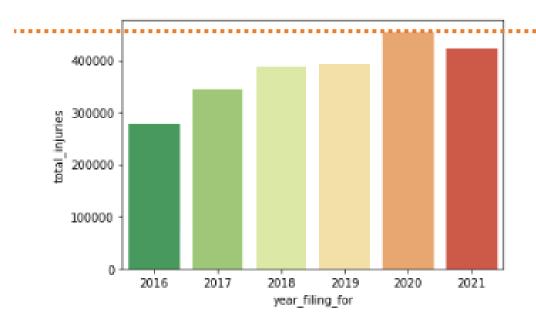
After processing the data, 2020 is the year with highest number of recorded injuries

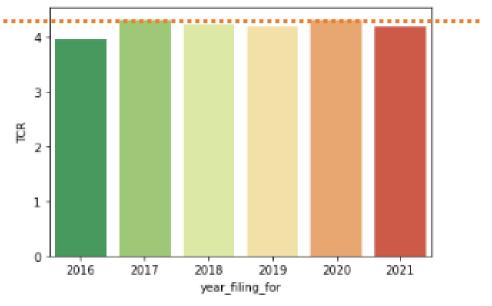




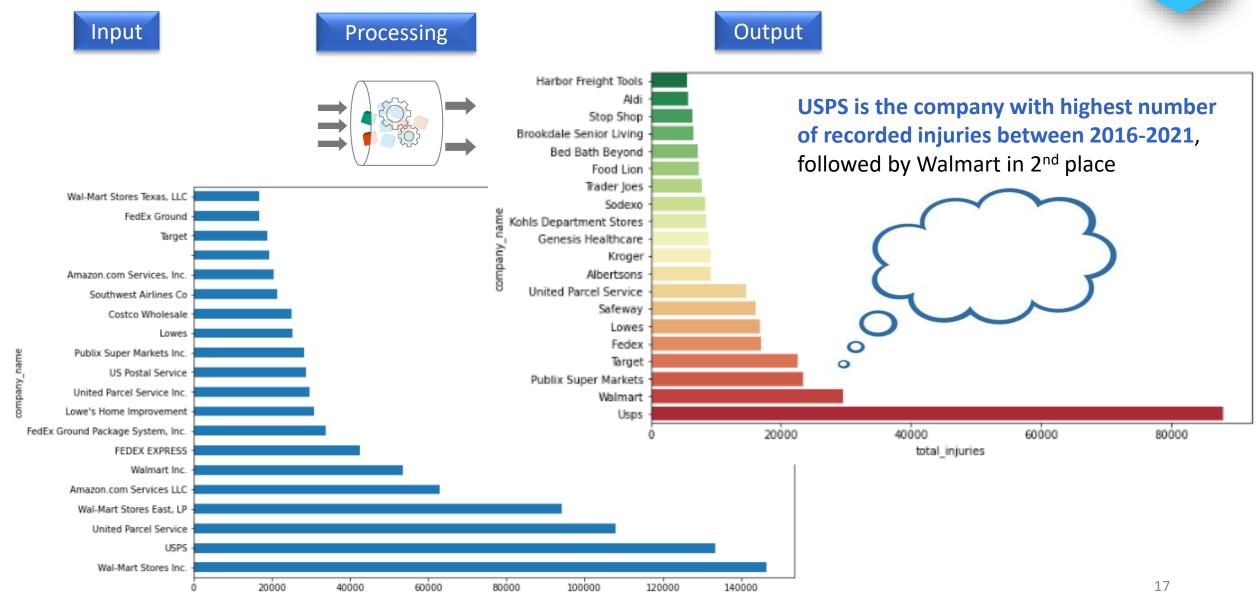
However, if we compare recorded injuries per year based on TCR incident rate, we can see highest TCR is maintained on year 2020, but with very slight difference between one year and another.







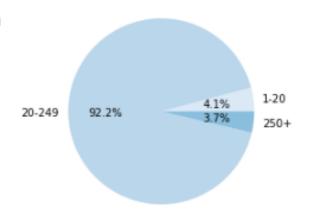


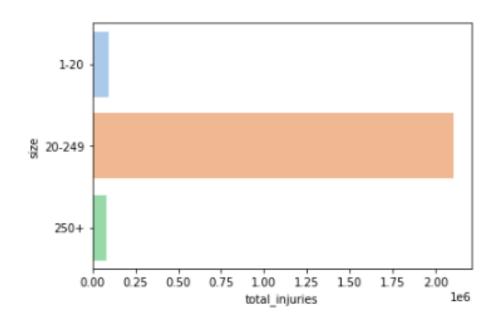




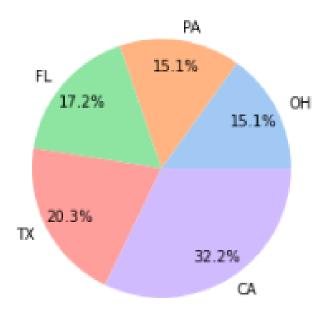
92.2% of the companies with recorded injuries are SME (Small Medium Enterprises)

(Small Medium Enterprises) with 20-249 employees



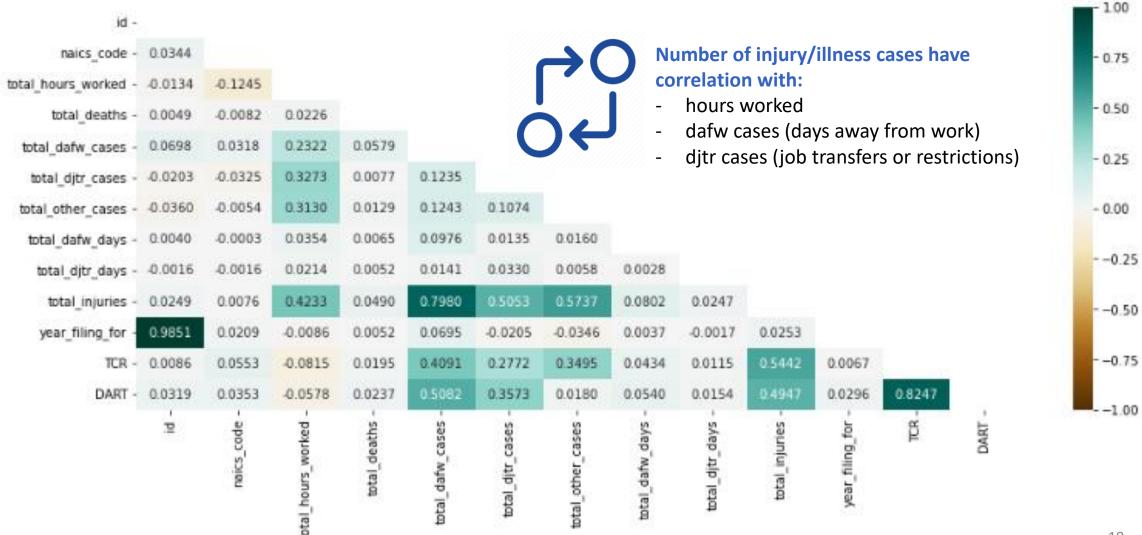


**53.5% of injuries/illnesses** occur only in the states of **California and Texas** 





#### Triangle Correlation Heatmap



### Conclusions



#### Wrapping up:

- 1. 2020 has the highest number of recorded injury/illness and TCR.
- 2. TCR is very similar for all recorded years.
- USPS is the company that registered highest number of total injuries, followed by Walmart.
- 4. 92.2% of the companies are SME (Small Medium Enterprises) with 20-249 employees
- 5. 53.5% of injuries/illnesses occur only in the states of California and Texas
- 6. There is correlation between injury cases and hours worked, dafw cases (days away from work) and djtr cases (job transfers or restrictions)





#### ... but the most important one:

Data Cleaning and Data Pre-processing part is essential. Fighting with your data, will make it to confess their secrets. Correct insights can only be extracted if you have good data.



# Thank you!

