

# **Exploring Geographic and Drug Data** from Annotated Case Reports

Presented by Clement Feyt, Kitu Komya, and Joel Perez

December 1, 2017

### Background(1)

- Millions of medical case reports published on-line
- Aggregation of textual knowledge using Natural Language Processing: incredible potential of new discoveries and improving evidence based medicine
- > Necessity of constituting a training set of labeled case reports
  - Manual annotation of 3000 case reports (thanks to David, Sanjana, Jessica, John, Travis, Anders, Joshua, Harry, Sarah, Clement, Dibakar and Michaela), of which 200 are still under quality control process

### Background(2)

- Multiple disease systems to explore
- > Promising avenues to analyze first are geographic and drug data:
  - How does drug usage compare between gender and age? (Joel)
  - How does location affect frequency of case reports within a certain disease system? (Kitu)

### Goals

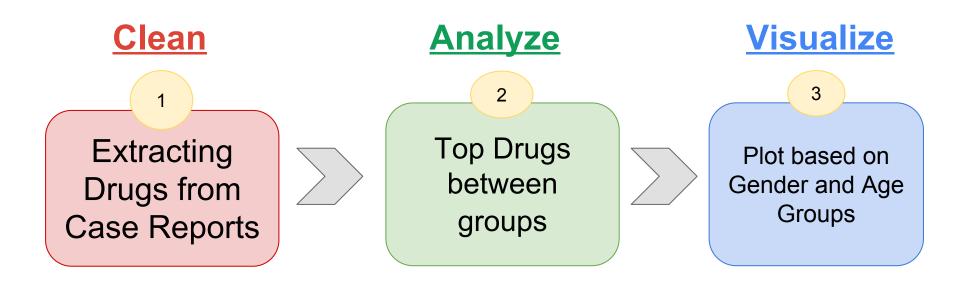
Text-mine from annotated data to extract relevant information

Analyze drug usage between Gender and Age(Joel)

3 Explore relationship between location and frequency of case reports within a certain disease system (Kitu)

Create a usable and interactive platform to present data (R Shiny)

## Joel's Workflow: Pharmacological drug Data





### **Extraction Process**

- Started with the drugs list dataset from National Library of Medicine
- Cleaning process:
  - Removed duplicates
  - Subsets:
    - e.g. "aspirin", "aspirins"
    - e.g. "Mesna", "product containing mesna", "product containing mesna medical product"
- Compared list to the case reports' Pharmacological Therapy column to extract the drug names



### **Analysis**

### Drug Usage:

What are the most frequently used drugs based on gender?

What are the most frequently used drugs based on age group?

Age Groups: 1 Age: 0 - 2

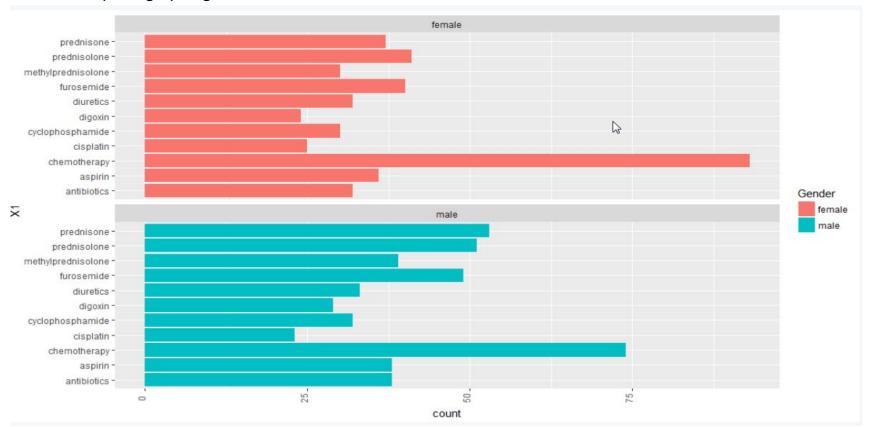
2 Age: 2 - 10

3 Age: 10-20

... Age: 20~



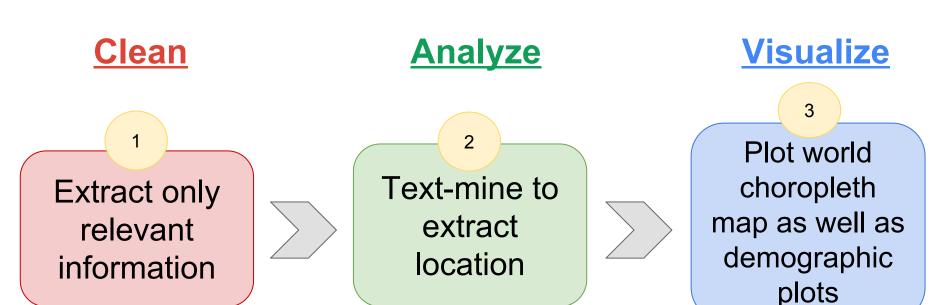
### Top drugs per gender



### 1001 (0105) 1010 (0106) 1010 (0106) 1011 (0107) 1011 (0107) Top Drugs per Age Group 2 prednisone prednisolone prednisoneprednisolone methylprednisolone prednisolone: methylprednisolone furosemide methylprednisolone furosemide diuretics furosemide diuretics digoxin diuretics digoxin cyclophosphamide cyclophosphamide cyclophosphamide cisplatin cisplatin cisplatin chemotherapy chemotherapy chemotherapy aspirin aspirin aspirin antibiotics antibiotics antibiotics : 5 prednisone prednisone prednisone prednisolone prednisolone prednisolone methylprednisolone methylprednisolone methylprednisolone furosemide furosemide furosemide diuretics diuretics diuretics -× digoxin digoxin digoxin cyclophosphamide cyclophosphamide: cyclophosphamide cisplatin chemotherapy cisplatin chemotherapy aspirin chemotherapy aspirin antibiotics antibiotics antibiotics : 10 20 30 0 8 prednisone prednisone prednisolone prednisolone methylprednisolone methylprednisolone: furosemide furosemide diuretics diuretics digoxin cyclophosphamide cisplatin cyclophosphamide chemotherapy chemotherapy aspirin aspirin antibiotics antibiotics -30 10 20 10 20 30 count



### Kitu's Workflow: Geographic Data





# **Extracting only relevant information**

CR ** Number	Institution
CCR1476	edmonton general hospital; university of alberta
CCR579	division of surgical oncology, department of surgery, n
CCR1633	department of pathology, university of arkansas for m
CCR1000	department of otolaryngology, head and neck surgery,
CCR1203	section of neuroradiology, clinic of neurosurgery, chris
CCR2976	department of pediatrics, yokohama city university sch
CCR2685	department of radiology, ohshima clinic, sakurada nishi
CCR1032	retina service, department of ophthalmology, massach
CCR606	from the departments of general and endocrine surger
CCR1237	department of ophthalmology, university of arkansas f
CCR1555	department of medicine, division of infectious diseases,
CCR2740	unità di pneumologia e terapia semi-intensiva respiratori
HCR001	divisions of cardiology and cardiac surgery, university
CCR292	cardiology department, complejo hospitalario universita

Hospital (	Institution_2
All	All
edmonton general hospital	university of alberta
division of surgical oncology, department of surgery, n	NA
department of pathology, university of arkansas for m	NA
0	NA
section of neuroradiology, clinic of neurosurgery, chris	NA
retina service, department of ophthalmology, massach	NA
from the departments of general and endocrine surger	NA
department of ophthalmology, university of arkansas f	NA
1	NA
1	NA
service de maladies infectieuses aigues, pôle maladies i	service de rhumatologie, assistance publique hôpitaux
section of oncopathology and regenerative biology, de	NA
department of orthopaedics, university of illinois at chic	NA
cardiovascular institute, hospital clínico san carlos, c/o	NA



### **Text-mining to extract location**

- > Ran into a lot of problems in extracting location
  - Dataframe had both cities and countries
  - Used a dataset of all cities first...3 mil+, so very inefficient
- Re-looked at dataset to find trends
  - Extracted all Country names and US state names
  - Extracted all Country abbreviations
  - Extracted major US cities
- > Some still left
  - Misspellings of cities or countries (ex: ilinois, or pekingchina)
  - Manually annotated rest
  - In the future, will extract from a hospital dataset (which is majority of data)



# Visualizing the geographic data + other demographics

# Let's demo it!



### **Summary**

- Location plays an important part in frequency of case reports
  - Japan!
- Demographics change over country as well as disease group
- > This interactive, geographic tool proves useful in finding new insights



### **Next Steps**

- Search "signs and symptoms" within diseases
  - Will require Natural Language Processing
- Explore how case reports are related to each other
- Perhaps standardize frequency of case reports to region's population