MethodologyPart1

June 20, 2022

[1]:
```
import sys

# append the directory of law module to sys.path list
sys.path.append('../modules/')
```

[2]:
```
import json
import re
from textwrap import wrap

import altair as alt
import altair_reveal as reveal
import arrest
import law
import numpy as np
import pandas as pd
import requests
from altair.expr import datum
from altair_saver import save
from scipy.stats import chi2_contingency
from scipy.stats.contingency import expected_freq

alt.themes.register('reveal', reveal.theme)
alt.themes.enable('reveal')
```

[2]:
```
ThemeRegistry.enable('reveal')
```

[3]:
```
def load_chart_json(file):
    with open(file) as jsonfile:
        data = json.dumps(json.load(jsonfile))
    new_chart = alt.Chart.from_json(data)
    return new_chart
```

1 Cross-city comparisons

1.1 Decision: Date range

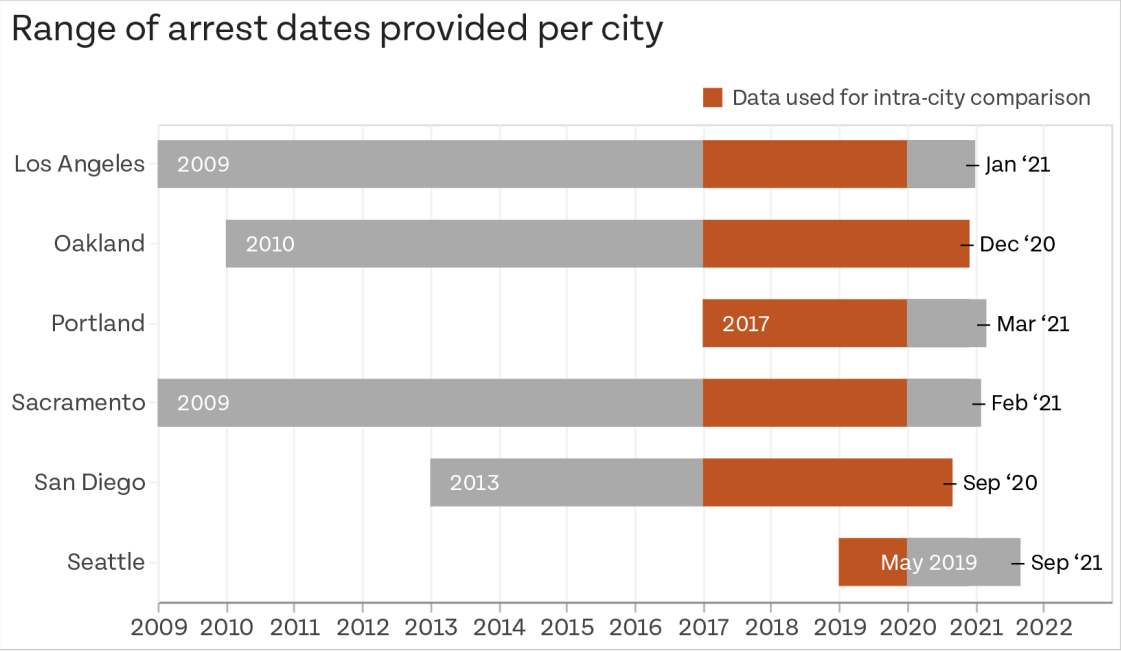
I received data from six cities in time for the story.

I'd requested ten years from each, but:

- Portland charged several hundred dollars for even this ~4-year subset.
- Oakland's began with 2010 because we sued for the data and so fulfillment started later than for other cities.
- San Diego could only provide data as far back as 2013, and fulfilled the request earlier than other cities (September 2020).
- Seattle could only provide data as far back as May 2019.

1.1.1 Approach: Compare a subset of "recent" dates

In the radio show, I cited specifics only for Portland, so I used the full range of data the agency provided. I have since compared arrests among cities for **2017 through the end of 2020**, where possible.



1.1.2 Concerns

San Diego San Diego is short three months (ending September 2020).

- For the purpose of visualization, **my approach is to include San Diego and add a note about it in chart methodologies**.

Seattle

- Seattle is short by much more; with a uniform end date of December 2020, Seattle represents 18 months of data. For the purpose of visualization, **my approach is to exclude Seattle from graphics and add a note in the overall arrest chart methodology.**

1.2 Decision: Juvenile data

Some cities did not provide data on arrests of minors.

1.2.1 Approach: Exclude all arrests of people who were under age 18 when they were arrested.

1.3 Decision: Categorizing housing status

1.3.1 No address information

Approach: Separate each city into unhoused, housed, and no information. Though I'd requested arrests per se, it appears that Los Angeles also provided citation data, as thousands of entries had no jail booking number attached. I contacted the Los Angeles Police Department Public Records Unit about this, and this was their response:

> Although your request is not a request for records, in the spirit of transparency and community relations, the answers to your questions are as follows:
>
> 1. I'd requested data regarding arrests, but if an entry has neither a Booking Number nor warrant information, does this mean that the entry represents a citation? I ask in part because these entries are also always without address information as well.
>
> The entries that have neither a booking number or warrant number are release from custody arrests. This means that the person was not physically booked, and therefore was not assigned a booking number. In these cases, the violator is issued paperwork similar to a citation. This is also why their residence address is not captured.

Concern I followed up with the San Diego Police Department public records administrator about the arrest data I received, and she reiterated that the city did not send citation data.

> The San Diego Police Department has confirmed that the records provided only include arrests as requested.

However, the "no information" proportion of arrests in this data is much higher than in any other city. I asked the same administrator about this April 28th, but as of today (May 5th, 2022), I have not received a response. I also contacted Seattle about its high proportion of such arrests and have also not received a response.

[4]:
```
story_df = pd.read_csv('../US/04_outputs/c05_nibrs_charge_sets_merged.csv',
                       dtype=str)
```

[5]:
```
seattle_df = pd.read_csv('../US/04_outputs/a01_seattle.csv',
                         usecols=['_arrest_id', '_arrest_date',␣
↪'_housing_status', '_city'])
```

[6]:
```
df = pd.concat([story_df, seattle_df], ignore_index=True)
```

[7]:
```
df.columns = [re.sub('^_', '', x) for x in df.columns]
```

[8]:
```
df['housing_status'] = df['housing_status'].str.title()
```

[9]:
```
df['simplified_housing_status'] = df['housing_status'].replace(
    {'No Information': 'Address missing or unknown',
     'Unknown': 'Address missing or unknown'})
```

1.3.2 Plot

[10]:
```
arrests_by_simplified_housing = df.groupby(['city',␣
↪'simplified_housing_status']).agg(
    arrests=('arrest_id', 'nunique')
)
```

[11]:
```
arrests_by_housing = df.groupby(['city', 'housing_status']).agg(
    arrests=('arrest_id', 'nunique'))
```

[12]:
```
arrests_by_housing
```

[12]:

city	housing_status	arrests
Los Angeles	Housed	747443
	No Information	379
	Unhoused	150216
	Unknown	67
Oakland	Housed	78659
	No Information	671
	Unhoused	5321
	Unknown	946
Portland	Housed	31982
	No Information	1603
	Unhoused	34486
	Unknown	951
Sacramento	Housed	126382
	No Information	302
	Unhoused	45194
	Unknown	811
San Diego	Housed	99013
	No Information	49545

```
              Unhoused          16403
              Unknown            1168
Seattle       Housed            25936
              No Information     3747
              Unhoused           4916
```

Aggregation

[13]:
```
arrests_by_simplified_housing = df.groupby(['city',␣
↪'simplified_housing_status']).agg(
    arrests=('arrest_id', 'nunique')
)
```

[14]:
```
arrests_by_housing = df.groupby(['city', 'housing_status']).agg(
    arrests=('arrest_id', 'nunique'))
```

[15]:
```
arrests_by_city = df.groupby(['city']).agg(arrests=('arrest_id', 'nunique'))
```

[16]:
```
percent_df = arrests_by_housing.div(arrests_by_city).reset_index()
```

[17]:
```
simplified_percent_df = arrests_by_simplified_housing.div(
    arrests_by_city).reset_index()
```

Generate field to sort by housing status

[18]:
```
c = dict(zip(['Unhoused', 'Housed', 'No Information',
              'Unknown', 'Address missing or unknown'], [1, 2, 3, 3, 3]))
```

[19]:
```
percent_df['_order'] = percent_df['housing_status'].replace(c)
```

[20]:
```
simplified_percent_df['_order'] =␣
↪simplified_percent_df['simplified_housing_status'].replace(
    c)
```

[21]:
```
simplified_percent_df
```

[21]:

	city	simplified_housing_status	arrests	_order
0	Los Angeles	Address missing or unknown	0.000497	3
1	Los Angeles	Housed	0.832245	2
2	Los Angeles	Unhoused	0.167259	1
3	Oakland	Address missing or unknown	0.018891	3
4	Oakland	Housed	0.918946	2
5	Oakland	Unhoused	0.062163	1
6	Portland	Address missing or unknown	0.037003	3
7	Portland	Housed	0.463360	2
8	Portland	Unhoused	0.499638	1

```
9    Sacramento  Address missing or unknown  0.006445       3
10   Sacramento                      Housed  0.731847       2
11   Sacramento                    Unhoused  0.261707       1
12    San Diego  Address missing or unknown  0.305263       3
13    San Diego                      Housed  0.596001       2
14    San Diego                    Unhoused  0.098737       1
15      Seattle  Address missing or unknown  0.108298       3
16      Seattle                      Housed  0.749617       2
17      Seattle                    Unhoused  0.142085       1
```

Chart

[22]:
```
simplified_arrests_by_housing = (
    alt.Chart(simplified_percent_df)
    .mark_bar(size=25)
    .encode(
        x=alt.X(
            'arrests:Q',
            axis=None,
            title=None,
            stack='zero'
        ),
        order='_order:Q',
        fill=alt.Color(
            'simplified_housing_status',
            legend=alt.Legend(
                orient='top',
                title=None,
                values=[
                    'Unhoused',
                    'Housed',
                    'No information/Unknown',
                ],
                titleLimit=0,
                labelLimit=0,
            ),
            scale=alt.Scale(
                domain=['Unhoused', 'Housed', 'Address missing or unknown'],
                range=['#004488', '#349AC2', '#CCCCCC'],
            ),
        ),
        opacity=alt.condition(
            datum.city == 'Seattle' or datum.city != 'Seattle',
            alt.value(0.5),
            alt.value(1)),
    )
)
```

Text

[23]:
```
simplified_arrests_text = (
    alt.Chart(simplified_percent_df)
    .mark_text(font='Tenon', fontSize=14, align='right', dx=-5)
    .encode(
        x=alt.X('arrests:Q', title=None, stack='zero'),
        order='_order:Q',
        color=alt.condition(
            datum.simplified_housing_status == 'Address missing or unknown',
            alt.value('black'),
            alt.value('white'),
        ),
        text=alt.Text('arrests:Q', format='.0%'),
    )
).transform_filter(datum.arrests > 0.04)
```

Base

[24]:
```
arrests_base_story = (
    simplified_arrests_by_housing + simplified_arrests_text
).properties(width=400, height=35, title=alt.TitleParams(text=datum.city)).
 ↪transform_filter(datum.city != 'Seattle')
```

[25]:
```
arrests_base_seattle = (
    simplified_arrests_by_housing + simplified_arrests_text
).properties(width=400, height=35, title=alt.TitleParams(text=datum.city))
```

Title, subtitle

[26]:
```
def custom_wrap(text, max_width):
    width = max_width
    wrapped = wrap(text, width)
    while ' ' not in wrapped[-1]:
        width -= 1
        wrapped = custom_wrap(text, width)
    return wrapped
```

[27]:
```
all_arrests_title = 'Police disproportionately arrest unhoused people in West␣
 ↪Coast cities'
```

[28]:
```
all_arrests_title_formatted = custom_wrap(all_arrests_title, 30)
```

[29]:
```
all_arrests_subtitle = 'From 2017 through 2020, unhoused people made up at most␣
 ↪an estimated 2% of the population in each of the following cities.'
```

[30]:
```
all_arrests_subtitle_formatted = custom_wrap(all_arrests_subtitle, 40)
```

[31]:
```
def facet_and_config(base, city_sort, title_str='Draft/Reference',␣
↪subtitle_str=None, title_size=28, subtitle_size=20):
    chart = (
        alt.layer(base)
        .facet(
            row=alt.Row(
                'city:N',
                sort=city_sort,
                title=None,
                header=alt.Header(
                    labelFontSize=15,
                    labelFont='Tenon',
                    labelOrient='top',
                    labelAlign='left',
                    labelAnchor='start',
                    labelPadding=5,
                ),
            )
        )
        .resolve_axis(x='independent')
        .configure_title(
            font='Tenon',
            fontSize=title_size,
            color='#222222',
            fontWeight=500,
            align='left',
            anchor='start',
            subtitleFont='Tenon',
            subtitleColor='#222222',
            subtitleFontSize=subtitle_size,
            subtitleFontWeight=300,
            subtitlePadding=10,
            subtitleLineHeight=24,
            offset=22,
        )
        .configure_axis(
            gridColor='#dddddd',
            title=None,
            titleColor='#666666',
            titleFontWeight=300,
            labelColor='#666666',
            labelFont='Tenon',
            labelFontSize=13,
            labelFontWeight=400,
            labelFlush=False,
            labelPadding=5,
            tickSize=6,
```

```
        )
        .configure_axisX(
            # labels=False,
            domainColor='#666666',
            tickColor='#666666')
        .configure_axisY(
            labels=False,
            domainColor='#f9f9f9',
            tickColor='#f9f9f9')
        .configure_legend(
            title=None,
            orient='top',
            direction='horizontal',
            offset=40,
            columnPadding=20,
            titleFont='Tenon',
            titleFontSize=16,
            titleFontWeight=400,
            labelAlign='left',
            labelFont='Tenon',
            labelFontSize=15,
            labelFontWeight=300,
            labelColor='#222222',
            labelBaseline='middle',
            rowPadding=10,
            symbolType='square',
        )
    )
    if subtitle_str == None:
        return chart.properties(
            title={
                'text': title_str,
            },
        )
    else:
        return chart.properties(
            title={
                'text': title_str,
                'subtitle': subtitle_str,
            },
        )
```

[33]:
```
facet_and_config(
    arrests_base_seattle,
    city_sort=['Portland', 'Sacramento', 'Los Angeles',
          'Seattle', 'San Diego', 'Oakland'],
    title_size=28,
```

```
    subtitle_size=20,
)
```

[33]: alt.FacetChart(…)

In story draft

[34]:
```
facet_and_config(
    arrests_base_story,
    city_sort=['Portland', 'Sacramento', 'Los Angeles', 'San Diego', 'Oakland'],
    title_str=all_arrests_title_formatted,
    subtitle_str=all_arrests_subtitle_formatted,
    title_size=28,
    subtitle_size=20,
)
```

[34]: alt.FacetChart(…)

---

2 The rest is to be restructured!

2.0.1 Categorization: Regex

Approach, 'Unhoused' I categorized arrest subjects as unhoused if their recorded address:

[3]:
```
regex_df = pd.read_csv('example_data/unhoused_regex.csv', dtype=str)
```

- **was** or **contained**:
  - "homeless" or "transient" or what I deemed to be typos thereof.
    - 0 TRANSIENT, 299 17TH STREET TRANSIENT

[4]:
```
regex_df[regex_df['_street_address'].str.contains('T[A-Z]+T|H[A-Z]+SS')].head()
```

[4]:

	city	_street_address
0	San Diego	NONE TRANSIENT
1	Oakland	TRAINSENT
2	Los Angeles	1942 TRANSUEBT
3	Seattle	00000 HOMELESS SEATTLE, WA 98104
4	Portland	HOMELESS

- The name of a social service or emergency shelter

[5]:
```
regex_df[regex_df['_street_address'].str.contains('GENERAL')].head()
```

[5]:
```
           city                                _street_address
20      Seattle     1234 GENERAL DELIVERY SEATTLE, WA 98101
30      Seattle    99999 GENERAL DELIVERY SEATTLE, WA 98105
46      Seattle   9999 GENERAL DELIVERY BREMERTON, WA 98337
51      Oakland                               GENERAL DELIVERY
53   Sacramento                              GENERAL DELLIVERY
```

[6]:
```
regex_df[regex_df['_street_address'].str.contains('CITY TEAM')].head()
```

[6]:
```
         city    _street_address
131   Oakland   CITY TEAM SHELTER
```

- The name of or reference to a correctional facility

[7]:
```
regex_df[regex_df['_street_address'].str.contains('JAIL|PRISON|RCCC')].head()
```

[7]:
```
            city            _street_address
315   Sacramento            DVI STATE PRISON
558      Oakland           CONTRA COSTA JAIL
583   Sacramento          1 CDCRSTATE PRISON
685      Oakland     SANTA CLARA COUNTY JAIL
737      Oakland   SAN FRANCISCO COUNTY JAIL
```

- **corresponded to an address of**:
  - a social service or emergency shelter
    - `5130 LEARY SEATTLE` (Ballard Food Bank)
  - a government-run social service
    - `2415 W 6TH ST` (LA County Department of Social Services)

Approach, 'Housed' I used regular expressions to find PO Boxes as well, because they're an easy pattern to match and it would save a lot of time and/or money on geocoding services. **I categorized arrests for which addresses were specific PO Box numbers as 'Housed.'**

Concern I can't know what proportion of people with PO Box numbers are actually housed, but I made this decision based on two premises: 1. PO Boxes cost money to reserve (in Portland, the cheapest size is $16 a month and the applicant has to pay for at least three months up front) 2. Applying requires two proofs of identication, one of which "must be traceable to the bearer (prove your physical address)."

2.0.2 Categorization: Geocoding

Data quality I geocoded addresses to more efficiently normalize address fields.

U.S. Census Bureau I geocoded addresses first by attempting to use the free (albeit slow, and less robust) U.S. Census Bureau [geocoding API]. This API returns metadata regarding whether an

address matched and, if it matched, whether the match is `exact` or `inexact`. **I used the output of `exact` matches only.**

Geocodio For the second pass, I used Geocodio. Geocodio returns metadata regarding a match's `accuracy type` and `accuracy score`.

Accuracy types, per Geocodio documentation:

> Accuracy types include:
>
> - **rooftop**: on the exact parcel
> - **point**: generally, in front of the parcel on the street
> - **range_interpolation**: generally, in front of the parcel on the street
> - **nearest_rooftop_match**: the nearest rooftop point if the exact point is unavailable
> - **intersection**: An intersection between two streets
> - **street_center**: A central point on the street
> - **place**: zip code or city centroid
> - **county**: county centroid
> - **state**: state centroid

Acccuracy scores:

> Accuracy scores are a reflection of the amount of differences between the input and the output. We generally recommend using results with an accuracy score above 0.8. Results below that threshold can indicate potential issues, such as formatting issues or incomplete addresses.
>
> - **1**: the exact input was returned
> - **0.8**: Very close to the input with minor changes made
> - **<0.6**: More significant changes made; use these results with caution

I used the following criteria for using outputs:

1. `Accuracy Type` must be `rooftop` or `range_interpolation` **and**
2. `Accuracy Score` must be >=.76

I found upon manual review that addresses were between .76 and .8 when the street names had an edit distance of about two characters, e.g. the input was `123 Brodway` and the output was `123 Broadway`.

Addresses to match on This is an excerpt from California's "HUD 2021 Continuum of Care Homeless Assistance Programs Housing Inventory Count Report." Note that the inventory includes both emergency shelter and permanent housing:

CoC Number: CA-600

CoC Name: Los Angeles City & County CoC

	Family Units[1]	Family Beds[1]	Adult-Only Beds	Child-Only Beds	Total Yr-Round Beds	Seasonal	Overflow / Voucher
Emergency, Safe Haven and Transitional Housing	**3,353**	**10,129**	**10,978**	**0**	**21,107**	**3,409**	**0**
Emergency Shelter	2,821	8,506	8,072	0	16,578	3,409	0
Safe Haven	0	0	400	0	400	n/a	n/a
Transitional Housing	532	1,623	2,506	0	4,129	n/a	n/a
Permanent Housing	**3,500**	**11,434**	**22,122**	**36**	**33,592**	**n/a**	**n/a**
Permanent Supportive Housing*	1,906	5,983	17,694	0	23,677	n/a	n/a
Rapid Re-Housing	1,318	4,545	2,646	0	7,191	n/a	n/a
Other Permanent Housing**	276	906	1,782	36	2,724	n/a	n/a
Grand Total	**6,853**	**21,563**	**33,100**	**36**	**54,699**	**3,409**	**0**

HUD tracks addresses of the service providers in the data that underlies these counts.

[8]:
```
hic = pd.read_excel(
    '../US/01_inputs/HUD/HIC/2019-Housing-Inventory-County-RawFile.xlsx',␣
 ↪dtype=str)
```

But the data is irregular:

[9]:
```
hic[(hic['HudNum'] == 'CA-600') & (hic['address1'].str.contains('9251'))][
    ['address1', 'city', 'state']
].sort_values(by=['address1'])
```

[9]:
```
                address1              city state
4950  9251 PIONEER BLVD.  SANTA FE SPRINGS    CA
5473  9251 PIONEER BLVD.  SANTA FE SPRINGS    CA
5475  9251 PIONEER BLVD.  SANTA FE SPRINGS    CA
5476  9251 PIONEER BLVD.  SANTA FE SPRINGS    CA
5477   9251 Pioneer Blvd  Santa Fe Springs    CA
5478   9251 Pioneer Blvd  Santa Fe Springs    CA
```

So I also geocoded all addresses of service providers that operate in the jurisdictions for which I have arrest data. I set another criterion, as well:

[10]:
```
hic[(hic['HudNum'] == 'CA-600') & (hic['address1'].str.contains('9251'))][
    ['Organization Name', 'address1', 'city', 'state', 'Project Type']
].sort_values(by=['address1'])
```

[10]:
```
                                     Organization Name           address1  \
4950  Community Development Commission of the County…  9251 PIONEER BLVD.
5473                                  The Whole Child  9251 PIONEER BLVD.
5475                                  The Whole Child  9251 PIONEER BLVD.
5476                                  The Whole Child  9251 PIONEER BLVD.
5477                                  The Whole Child   9251 Pioneer Blvd
5478                                  The Whole Child   9251 Pioneer Blvd

                city state Project Type
4950  SANTA FE SPRINGS    CA          RRH
```

```
5473  SANTA FE SPRINGS    CA          PSH
5475  SANTA FE SPRINGS    CA          RRH
5476  SANTA FE SPRINGS    CA          RRH
5477  Santa Fe Springs    CA           ES
5478  Santa Fe Springs    CA          RRH
```

One address can correspond to arbitrarily many organizations and, more importantly, greater than one `Project Type`. So after geocoding, I also produced sets of each `Project Type` recorded for an address:

[11]:
```
hic_processed = pd.read_csv(
    '../US/04_outputs/c02_hic_west_coast_geocoded_with_type.csv', dtype=str)
```

[12]:
```
hic_processed[hic_processed['_geocodio_street_address'].str.contains(
    '^9251')][['_geocodio_street_address', '_project_types', '_subcategory',␣
 ↪'_category']]
```

[12]:
```
     _geocodio_street_address _project_types   _subcategory  _category
3538        9251 PIONEER BLVD   RRH; PSH; ES  mixed support  sheltered
```

Because the above address provides both emergency shelter and permanent supportive housing, **I did not categorize this address as "unhoused."** I did, however, make a note of the subcategory for future reference.

From the set of HIC site addresses, **I categorized each as "unhoused" only if the only recorded Project Type was "ES" (Emergency Shelter)**:

[13]:
```
hic_processed[hic_processed['_category'] ==
              'unhoused']['_project_types'].unique()
```

[13]:
```
array(['ES'], dtype=object)
```