TriMet Ridership and Housing Value Mapping methods

Transit ridership data

- We started by making a spatial point layer of all TriMet stops (current and historic) and their average total weekly ons and offs for the fall quarter, for each year of interest[1].
    - Portland Streetcar was not included as this is not a TriMet service.
- For each year, we aggregated these stops to a hexagonal grid by summing weekly ons and offs for all stops in each grid cell.
- We aggregated to a hexagonal grid because:
    - It makes spatial patterns easier to visualize across our transit district.
    - In some cases, stops have changed locations, or light rail stops have largely replaced bus stops. This makes it problematic to calculate change for each individual stop. By aggregating to a grid, we sidestepped this issue.
- Hexagon grid details:
    - We used a grid of regular hexagons that were ½ mile per side, with an area of around 100 acres each. We tried several grid resolutions and found that this one worked well for our region.
    - The extent we used was larger than our current transit district, because it needed to include all historic and current TriMet stops, including a few in areas where lines no longer exist.
    - The grid was creating using an ArcMap Add In created by Tim Whiteaker of The University of Texas at Austin, available here: https://www.arcgis.com/home/item.html?id=03388990d3274160afe240ac54763e57
- Once we had calculated average weekly on/off totals for each hex (again, broken out by year), we calculated absolute change between years.
- Note that not all grid cells have ridership data for both the before and after period shown in the map. If they do not, they have a value of "no data" and are transparent in the map.

Housing price data

- To better understand changing spatial patterns in housing costs, we used a tax lot data set that covers our region.[2]
    - It is maintained by the Oregon Metro Data Resource Center and is available here: http://rlisdiscovery.oregonmetro.gov/?action=viewDetail&layerID=41
    - For each taxlot, the shapefile has an estimated real market value (land and buildings), which is based on comparable sales and should reflect trends in real estate value.
    - It has been regularly updated and consistent since the 1990s, and Metro provided us with a fall snapshot for all years of interest
- Methods:
    - To ensure that we were comparing apples to apples, we only looked at Single Family Residential (SFR) taxlots across the entire district.
    - We normalized each SFR taxlot's real market value by the lot size.
    - For each ~100 acre hexagon, we then found the median area-normalized SFR real market value, for each year of interest.

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[1] We looked at change from 2001, 2009, and 2014, to 2016. We found that the period from 2001-2016 was the most telling.

[2] We considered using income levels, but decided against it because those are only available at the census tract level, which wasn't fine grained enough for our purposes.

    - From there, we could calculate percent change between years.
- Notes on the map
    - Note that not all grid cells have SFR housing value data for both the before and after period shown in the map. If they do not, they have a value of “no data” and are transparent in the map.
    - Some of the suburban areas that show the most dramatic increases in SFR median value are places where new construction occurred during the time period displayed.
    - We found a visually striking pattern of slower housing value increase east of 1-205 in Portland for the period 2001-2016.

Comparing worst quartiles

- To get a better understanding of how spatial patterns in ridership change and housing value change might relate, for each dataset we broke the percent change from 2001-2016 up into quartiles (4 ordered groups with roughly equal numbers).
    - The worst quartile for ridership change were the hexagons with the biggest decreases
    - The worst quartile for housing value change were the hexagons with the biggest increases
- We mapped out the worst quartile hexagons, and the hexagons that were in the worst quartile for both. We found that theses appeared to be clustered in the central city.

Note that most calculations were completed using Python scripts with the ArcPy library. These scripts can be shared if anyone is interested.