2024/9/13(金)
BMSS Final presentation

松山市中心市街地における 歩行者空間整備が交通手段選択に与える影響

The Influence of Pedestrian Space Development on Transportation Choices in the Central Area of Matsuyama City

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Background

・Walking along Hanazonomachi Street and Okaido Street in Matsuyama, We had an impression that there were many pedestrians.

・A pedestrian space in front of Matsuyama Station is also scheduled to be developed.

Study of the impact of pedestrian space development on transportation choices

Hanazono-machi Street (2024/8/1)

Renewal Plan in front of Matsuyama Station

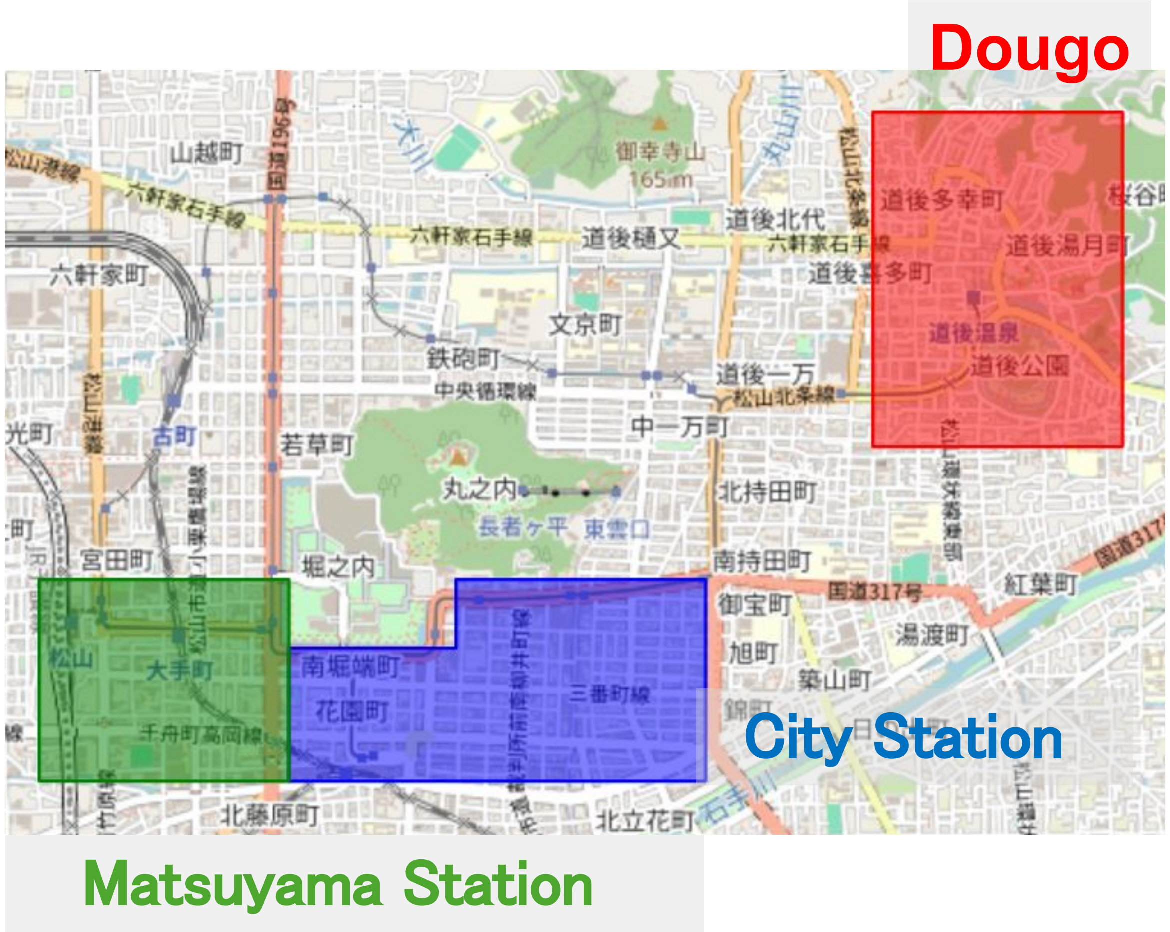
Policy Analysis

Hanazono-machi Street and Main Street are well maintained
Matsuyama City Station Area

Maintenance was done in front of Dougo Onsen Station
Dougo Area

Renewal will take place in the future
Matsuyama Station area

Basic analysis was conducted for each of the above three areas.

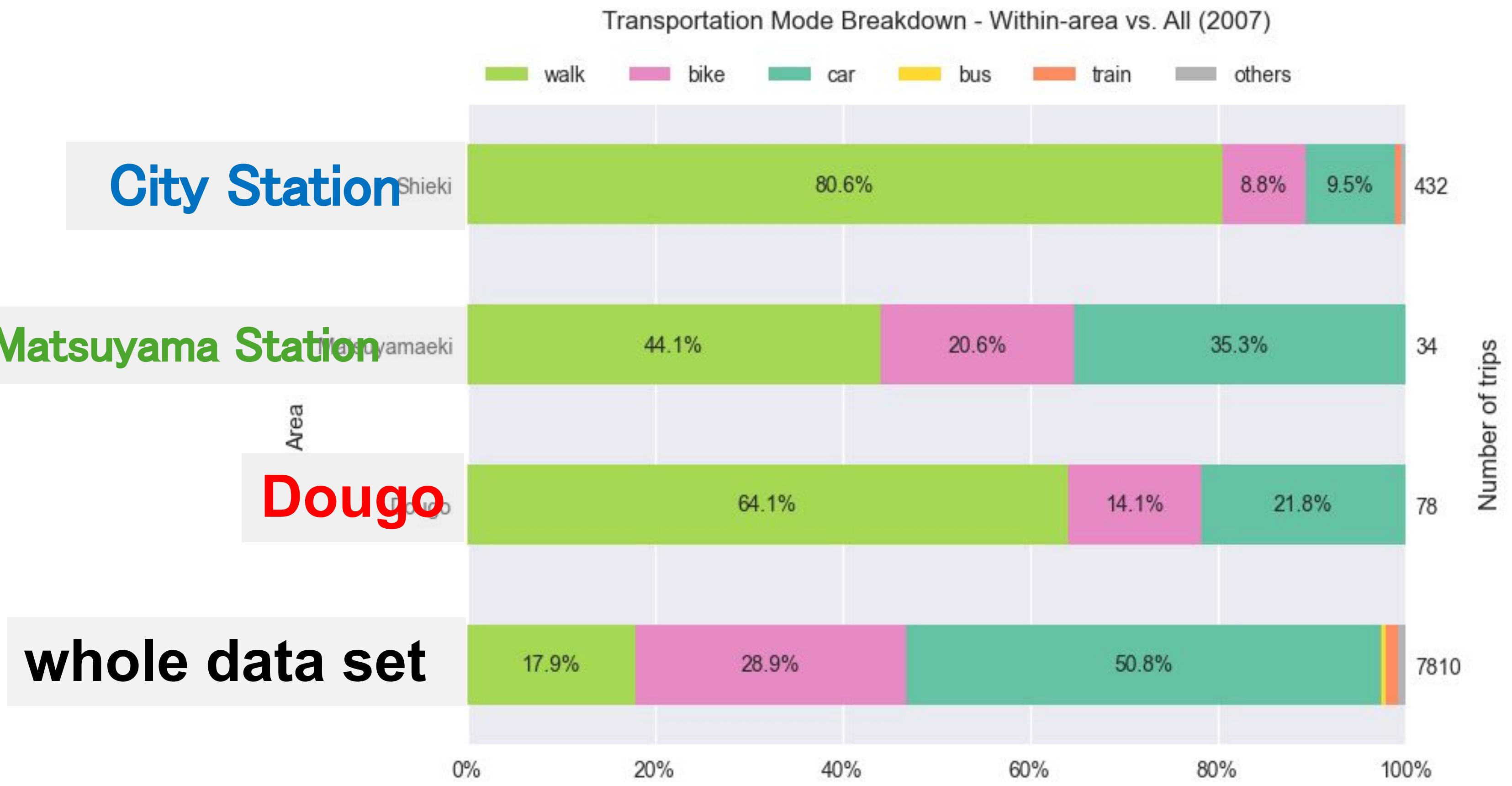


Data Aggregation

Proportion of Transportation Choices by Area

Data：trip.csv

within-area travels



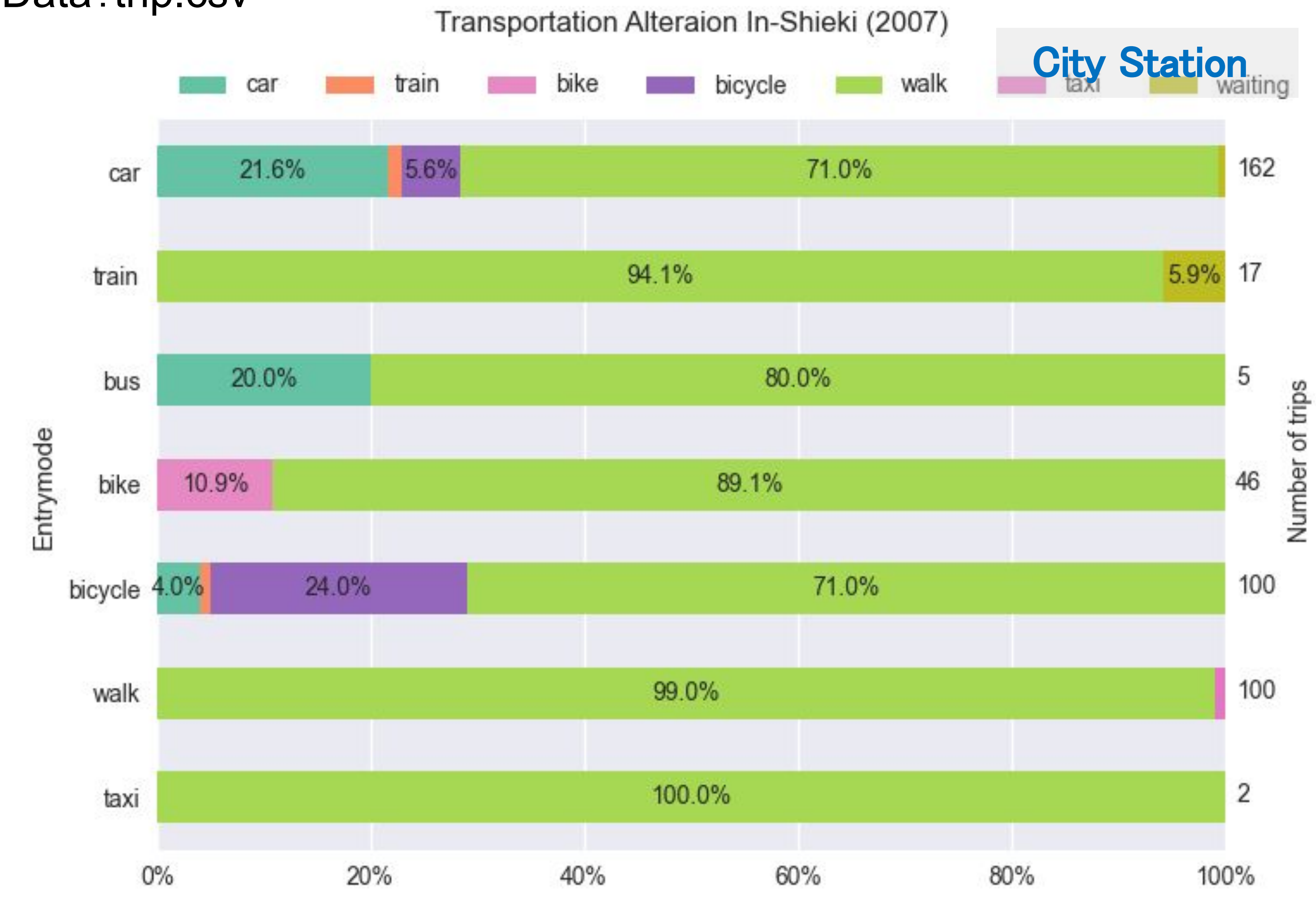
The proportions of pedestrian choices in the City Station and Dougo areas are higher than it in the Matsuyama station area.

Data Aggregation

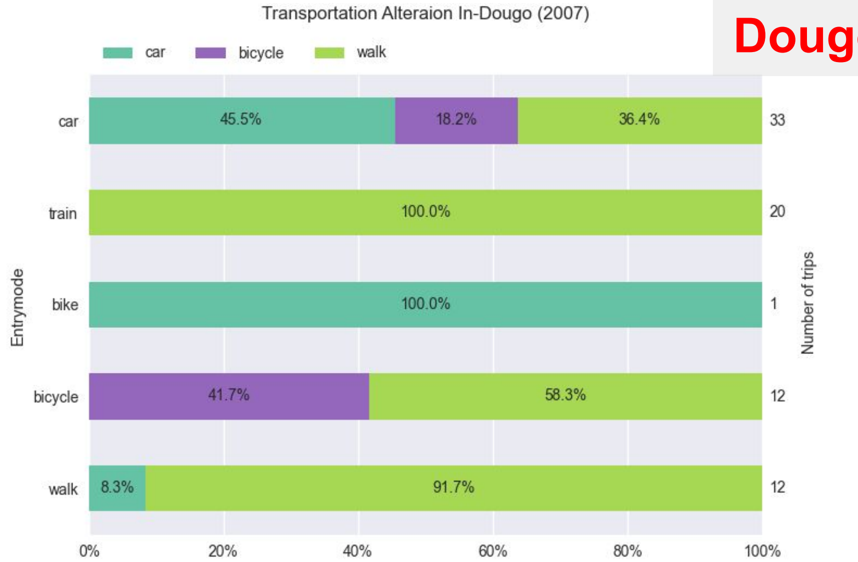
Entry-mode and Within-area mode

Data：trip.csv

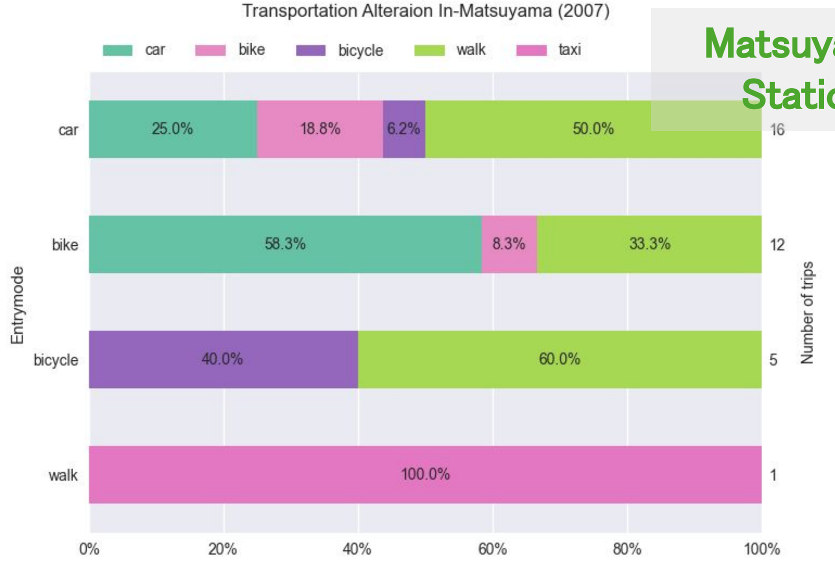
City Station



Dougo



Matsuyama Station



Analysis of comments of the links

Data：entry.csv

```
車が混んでいる。最悪。やっぱり、電車にした方がよかったかな〜。荷物が多いし、子ど
もも小さいので、仕方ない。
['車', 'が', '混む', 'で', 'いる', '。', '最悪', '。', 'やっぱり', '、', '電車',
'に', 'する', 'た', '方', 'が', 'よい', 'た', 'か', 'な', '〜', '。', '荷物', 'が
', '多い', 'し', '、', '子ども', 'も', '小さい', 'ので', '、', '仕方', 'ない', '
。']
-0.75
```

Based on the references (Kobayashi, 2005) and (Higashiyama, 2008), a dictionary is created to classify words into Positive, Negative, and Neutral categories.

↑An example of a negative comment
Result of morphological analysis with MeCab

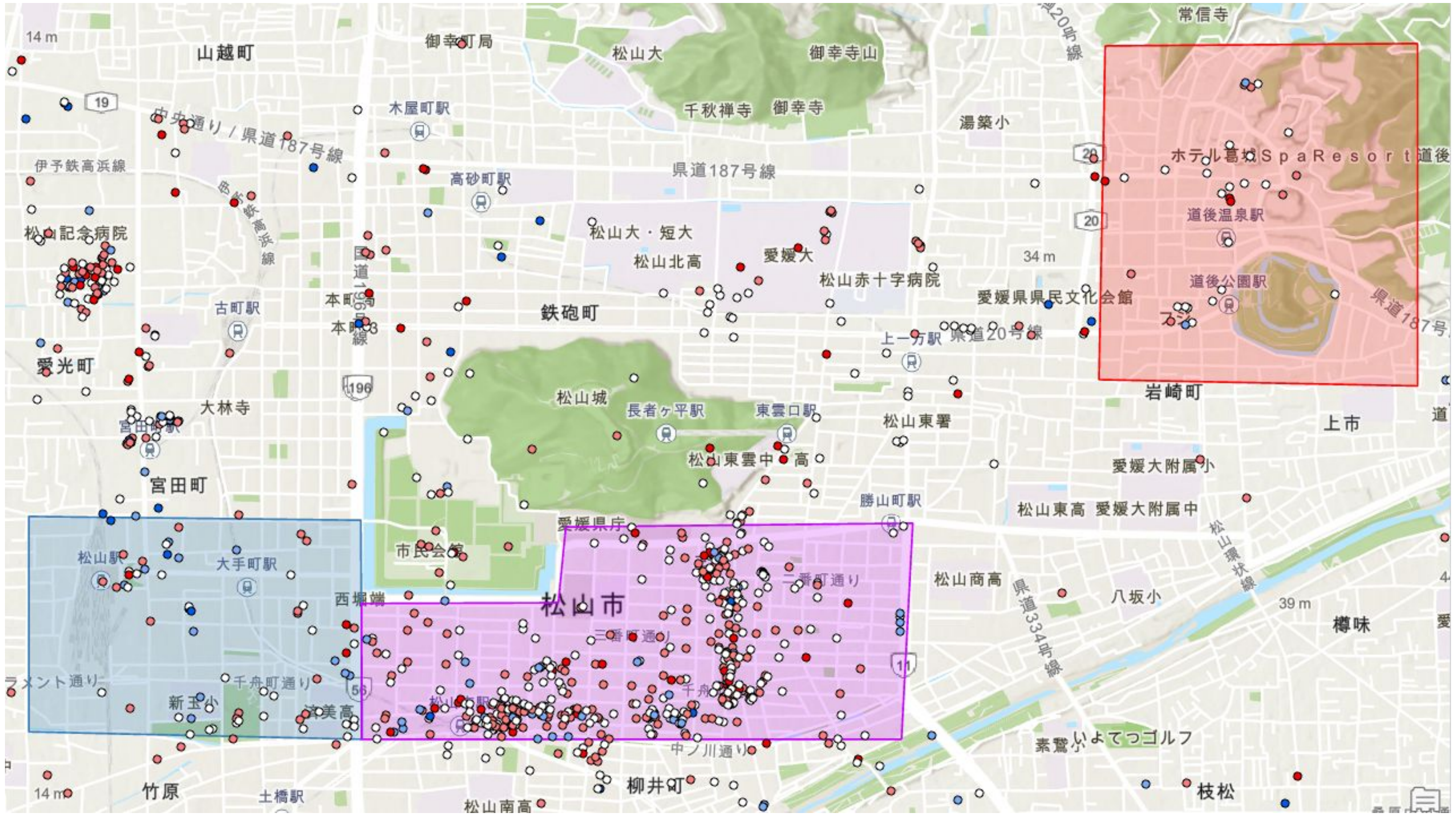
Using the dictionary, each comment is rated on a scale from −1.0 to 1.0.
(−1.0: very negative, 1.0: very positive).

Take the average of the ratings for these comments separately for positive and negative values, and the result indicates the rate of positive and negative impressions of the link.

Basic Analysis

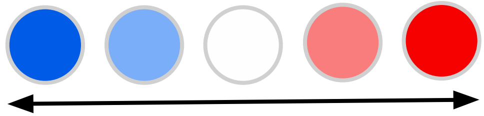
LORE FC

Data：entry.csv



Example:
“ツタヤにてCDをレンタルしました。
ココは古めのタイトルが充実してるので、
昔の曲を聴きたい時、助かります。”
(I rented a CD at Tsutaya. This place has a great selection of older titles, so it’s really helpful when I want to listen to old songs.)

” →0.667 positive ”

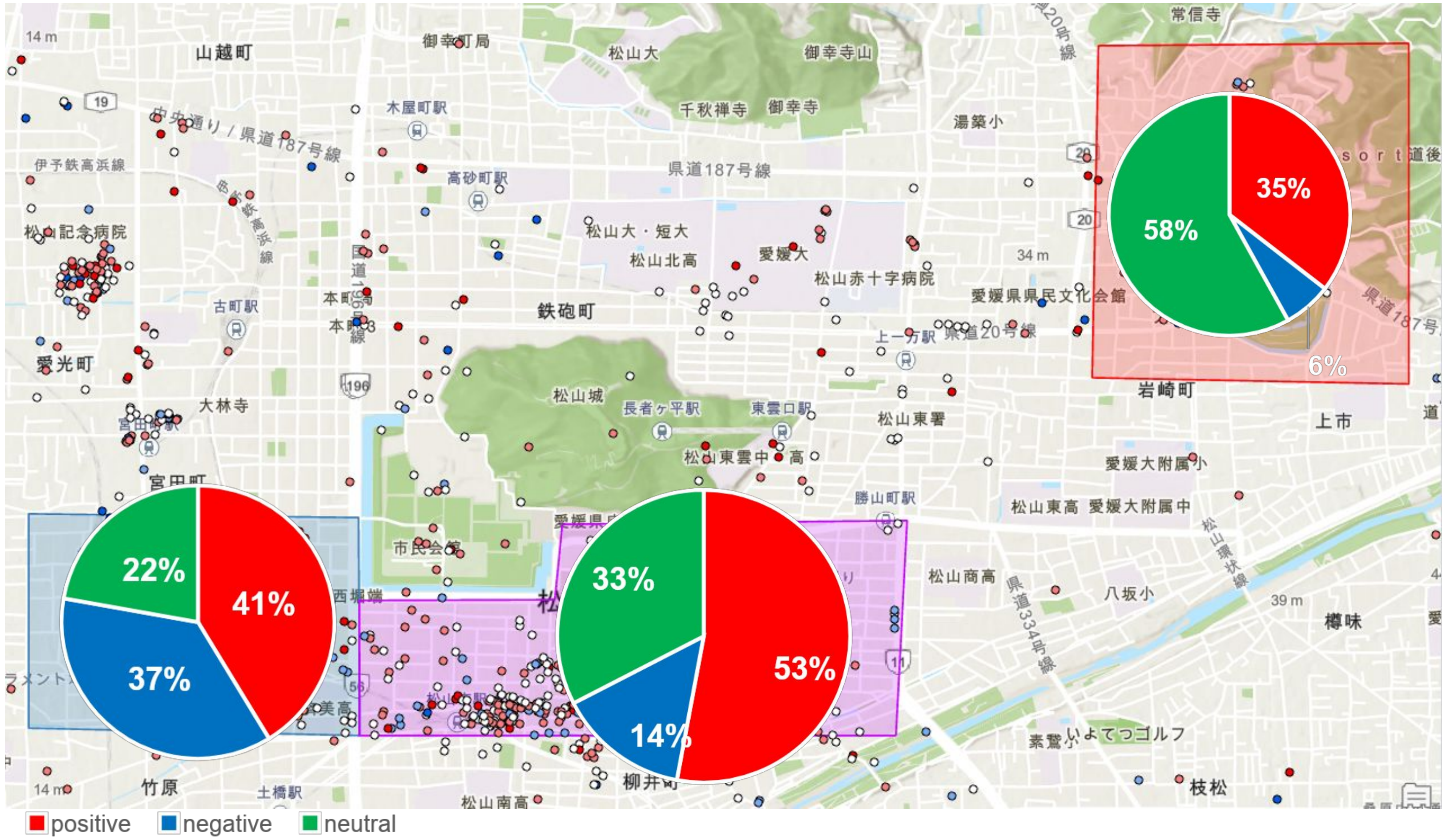


negative(−1)　(0)　positive(+1)

Many comments in areas where commercial facilities are concentrated.

Basic Analysis

Data：entry.csv



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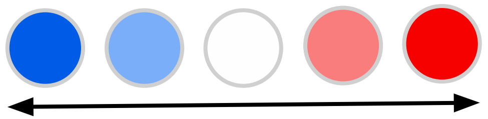
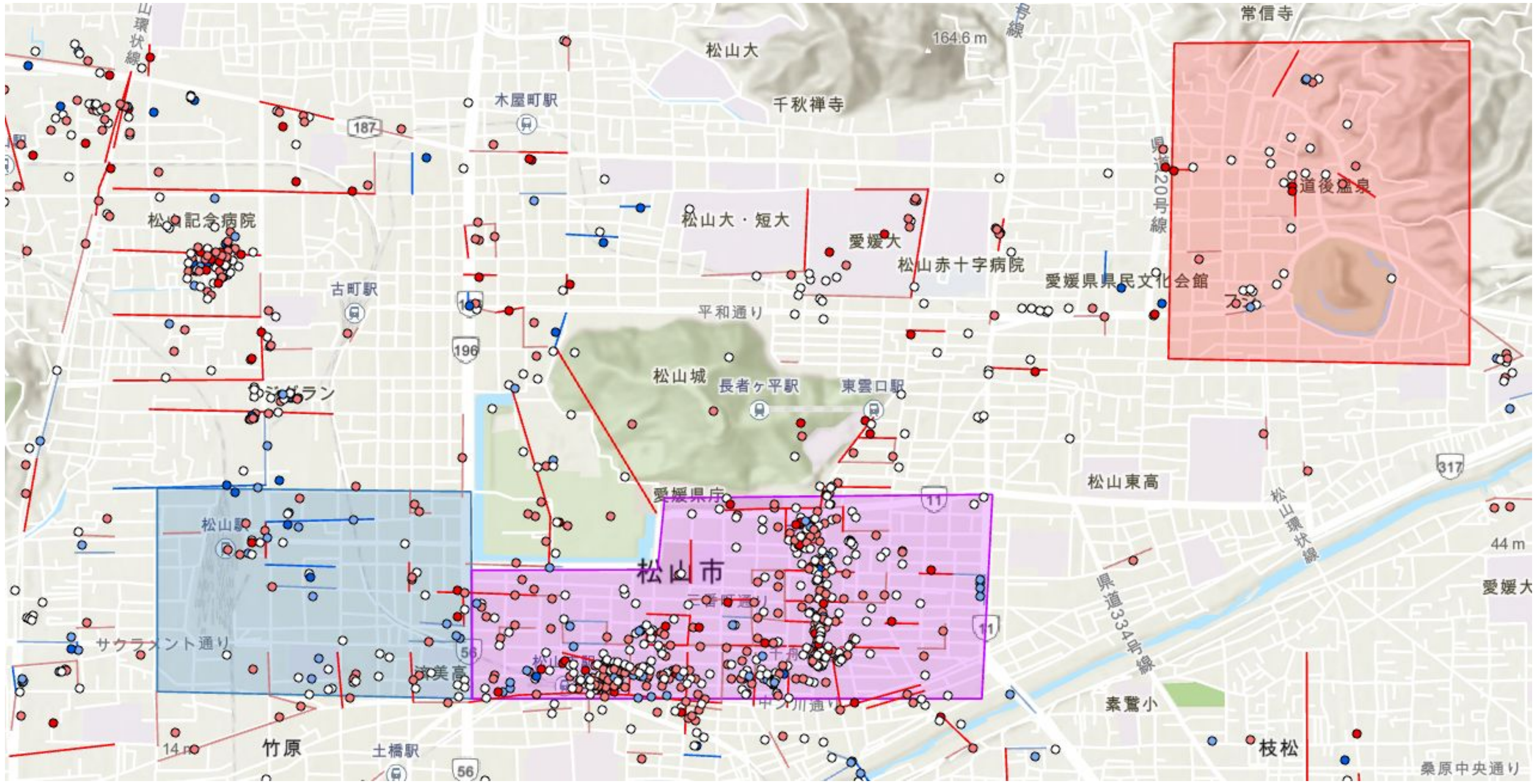


Many comments in areas where commercial facilities are concentrated.

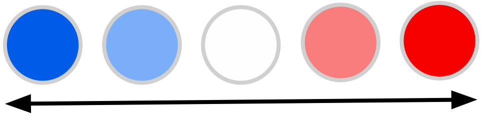
Basic Analysis

LORE FC



Add values to the nearest link from each point

Calculate the average and generate impressions for each link



negative(−1) (0) positive(+1)

Many comments in areas where commercial facilities are concentrated.

Model Formulation

LORE FC

Multinomial logit model (within-trip mode choice model)

$$U_{car} = b_1 + d_1 \cdot \boxed{TravelTime\,(car)} + m_1 \cdot \boxed{EntryModeDummy(car)}$$

$$U_{bike} = b_2 + d_1 \cdot \boxed{TravelTime\,(bike)}$$

$$U_{bicycle} = b_3 + d_1 \cdot \boxed{TravelTime\,(bicycle)}$$

$$U_{walk} = d_1 \cdot \boxed{TravelTime\,(walk)} + \boxed{f_1 \cdot PositiveImp + f_2 \cdot NegativeImp} + m_2 \cdot \boxed{EntryModeDummy(train)}$$

Model Formulation

Multinomial logit model (within-trip mode choice model)

$$
\begin{aligned}
U_{car} &= b_1 + d_1 \cdot TravelTime\,(car) + m_1 \cdot EntryModeDummy(car) \\
U_{bike} &= b_2 + d_1 \cdot TravelTime\,(bike) \\
U_{bicycle} &= b_3 + d_1 \cdot TravelTime\,(bicycle) \\
U_{walk} &= d_1 \cdot TravelTime\,(walk) + f_1 \cdot PositiveImp + f_2 \cdot NegativeImp \\
&\quad + m_2 \cdot EntryModeDummy(train)
\end{aligned}
$$

$TravelTime$: average speed of this mode × trip's travel distance

Model Formulation

LORE FC

Multinomial logit model (within-trip mode choice model)

$$U_{car} = b_1 + d_1 \cdot \boxed{TravelTime\ (car)} + m_1 \cdot \boxed{EntryModeDummy(car)}$$

$$\begin{cases} 1, & came\ to\ the\ area\ by\ car \\ 0, & not\ by\ train \end{cases}$$

$$U_{bike} = b_2 + d_1 \cdot \boxed{TravelTime\ (bike)}$$

$$U_{bicycle} = b_3 + d_1 \cdot \boxed{TravelTime\ (bicycle)}$$

$$U_{walk} = d_1 \cdot \boxed{TravelTime\ (walk)} + \boxed{f_1 \cdot PositiveImp + f_2 \cdot NegativeImp}$$
$$+ m_2 \cdot \boxed{EntryModeDummy(train)}$$

$$\begin{cases} 1, & came\ to\ the\ area\ by\ train \\ 0, & not\ by\ train \end{cases}$$

$TravelTime$: average speed of this mode × trip's travel distance

Model Formulation

Multinomial logit model (within-trip mode choice model)

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$$U_{walk} = d_1 \cdot TravelTime\ (walk) + f_1 \cdot PositiveImp + f_2 \cdot NegativeImp + m_2 \cdot EntryModeDummy(train)$$

$$\begin{cases} 1, & came\ to\ the\ area\ by\ train \\ 0, & not\ by\ train \end{cases}$$

Impressions of trip i = $\dfrac{\sum Impressions\ of\ links\ in\ trip_i}{Number\ of\ links\ in\ trip_i}$

$TravelTime$: average speed of this mode × trip's travel distance

Results

Multinomial logit model (within-trip mode choice model)

5%有意

	explanatory variables	parameter value	t value
b_1	定数項_車	13.084	6.396
b_2	定数項_バイク	13.608	5.372
b_3	定数項_自転車	-2.643	-10.348
d	所要時間	-0.002	-0.136
f_1	印象_ポジティブ	-16.021	-2.075
f_2	印象_ネガティブ	-56.271	-3.011
m_1	来訪手段ダミー_車	0.796	0.951
m_2	来訪手段ダミー_電車	19.251	5.134
	サンプルサイズ	289	
	初期尤度	-400.639	
	最終尤度	-64.354	
	尤度比	0.839	
	補正済み尤度比	0.819	

ネガティブの影響は強く働く
→ネガティブ要素の改善が効果的
The positive influence is having a negative effect.
→ Does having more positive comments lead to a lower utility of walking??
ポジティブの影響が負に働いてしまっている
→推定がうまくいっていない？？
The negative influence is strong.
→ Improving negative factors is effective.

尤度比は0.839と高い
→よく再現できている
The likelihood ratio is 0.839, which is high.
→ It is well-replicated (well-fitted).

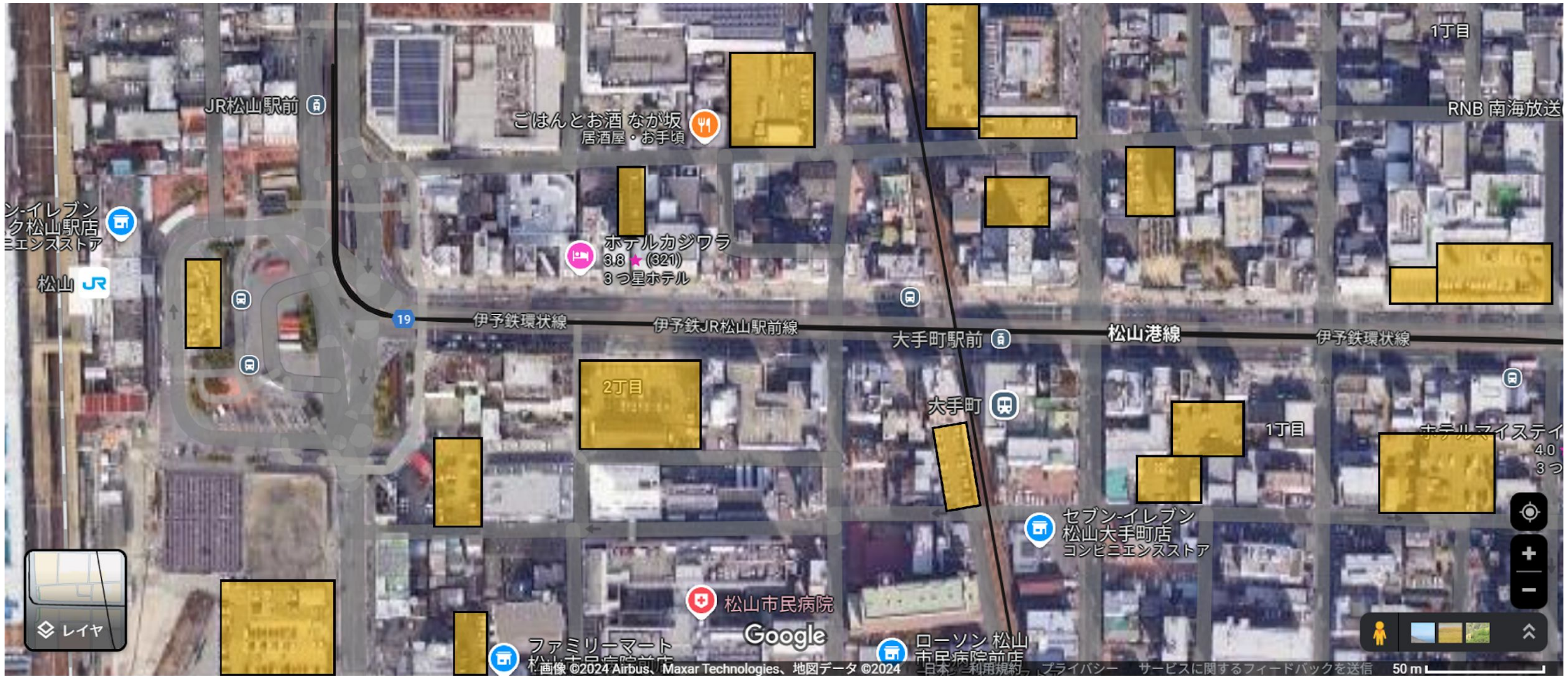
Results

LORE FC

Main results：Negative image has a strong influence on mode choice

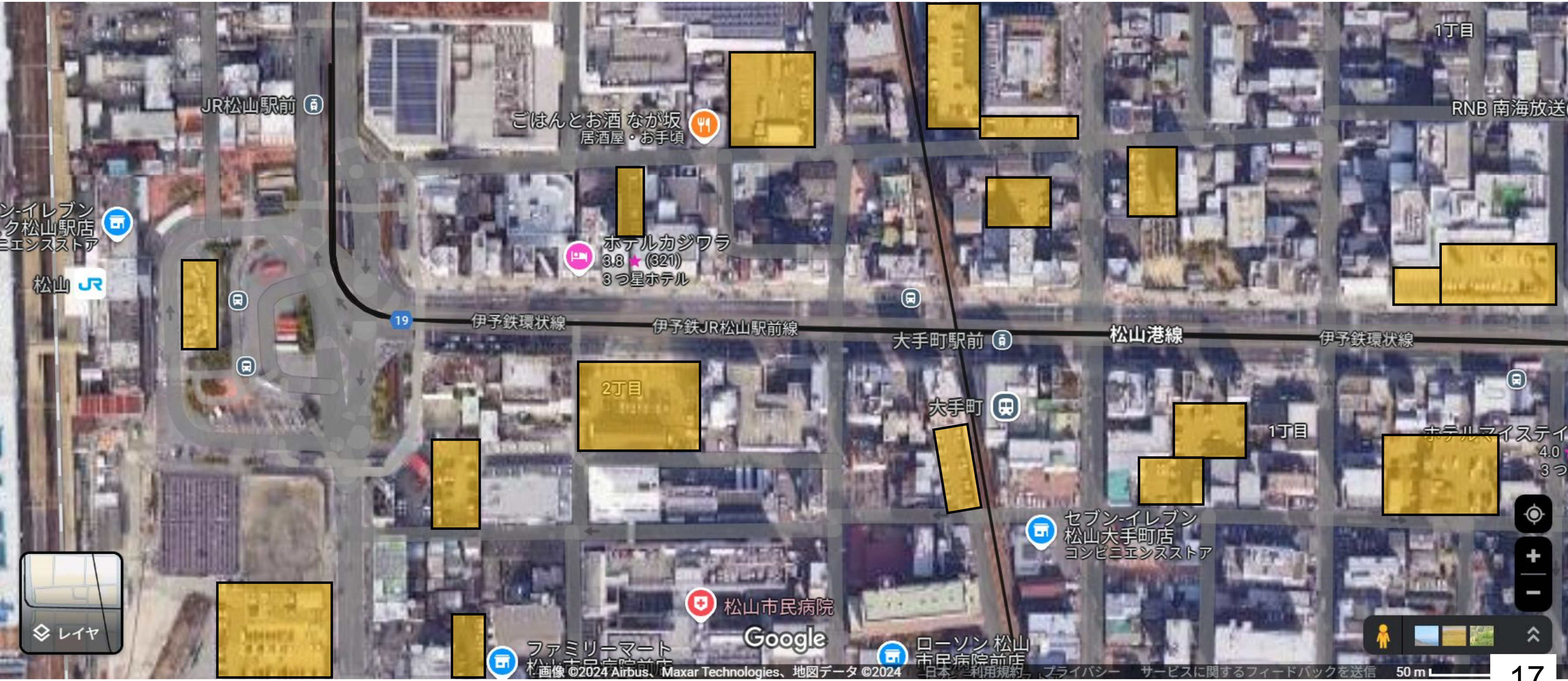
→We should clean up a negative image more than make a positive image

Ex. Parking lots near JR Matsuyama sta.



仮)ポジネガをどうモデルに入れてるか

We should reduce the space of parking lot



モデルの方針

多項ロジットモデル(域内移動の交通手段選択モデル)

$$U_{walk} = \text{定数項} + \text{経路距離} + \text{歩行者空間整備距離} + \text{印象} + \text{来訪手段ダミー}$$

$$U_{bicycle} = (\text{同上})$$

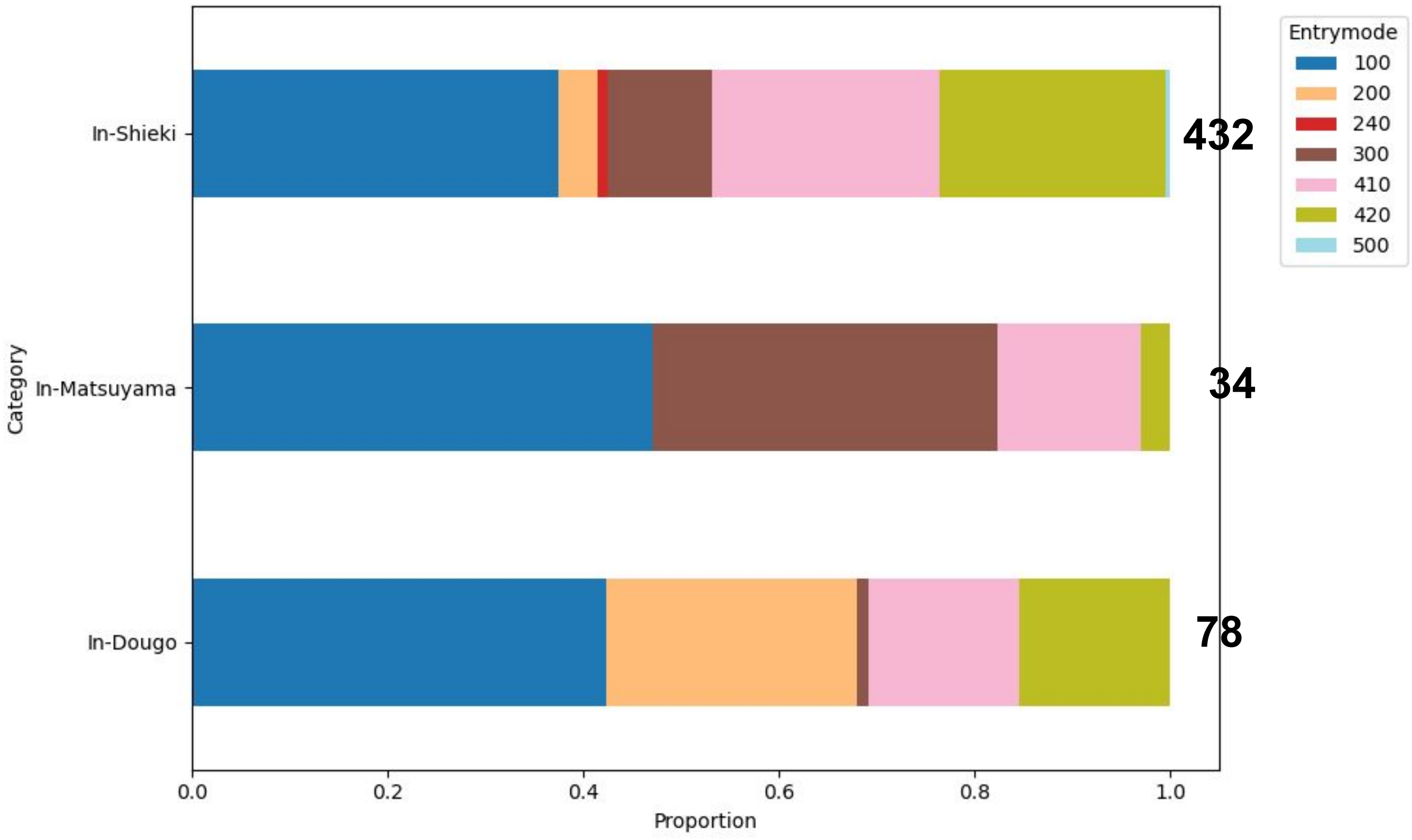
$$U_{bike} = (\text{同上})$$

$$U_{car} = (\text{同上})$$

トリップの発着位置から
最短経路を算出

最短経路で通過したリンクから、
コメントのポジ/ネガ指標を反映

エリアに来た交通手段

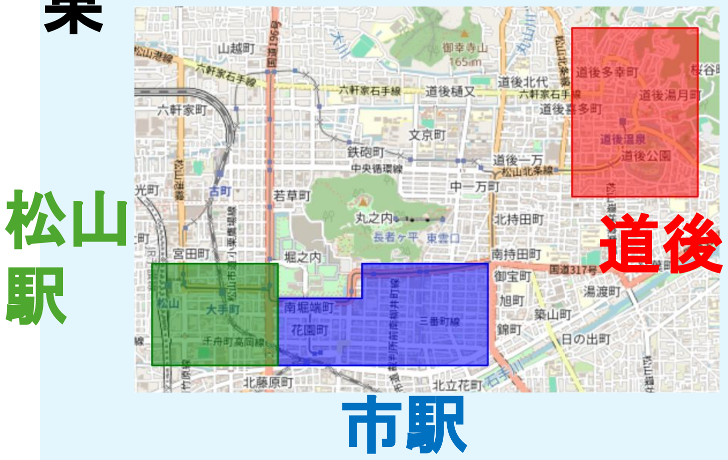


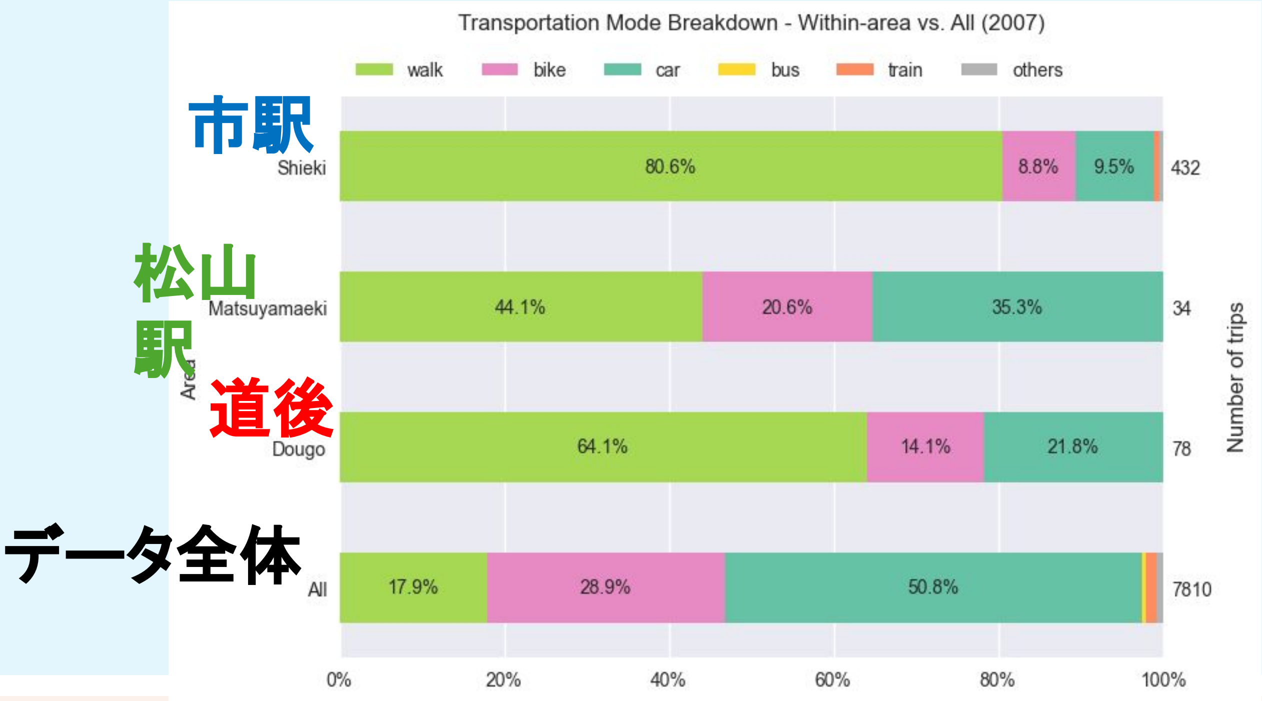
Entrymode
100
200
240
300
410
420
500
In-Shieki
In-Matsuyama
In-Dougo
Category
432
34
78
0.0
0.2
0.4
0.6
0.8
1.0
Proportion

①背景

・松山の花園町通りや大街道を歩いて、歩行者が多い印象を受けた。
・松山駅でも今後歩行者空間整備の予定。
→松山市駅、松山駅、道後温泉の3エリア別に基礎分析を実施。

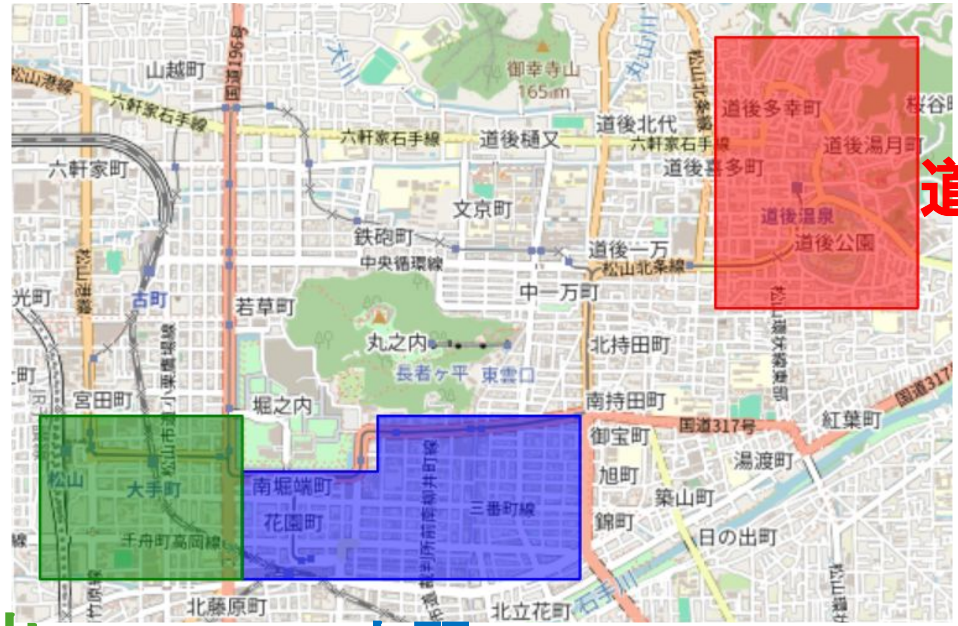
②基礎分析の結果





③モデルの方針

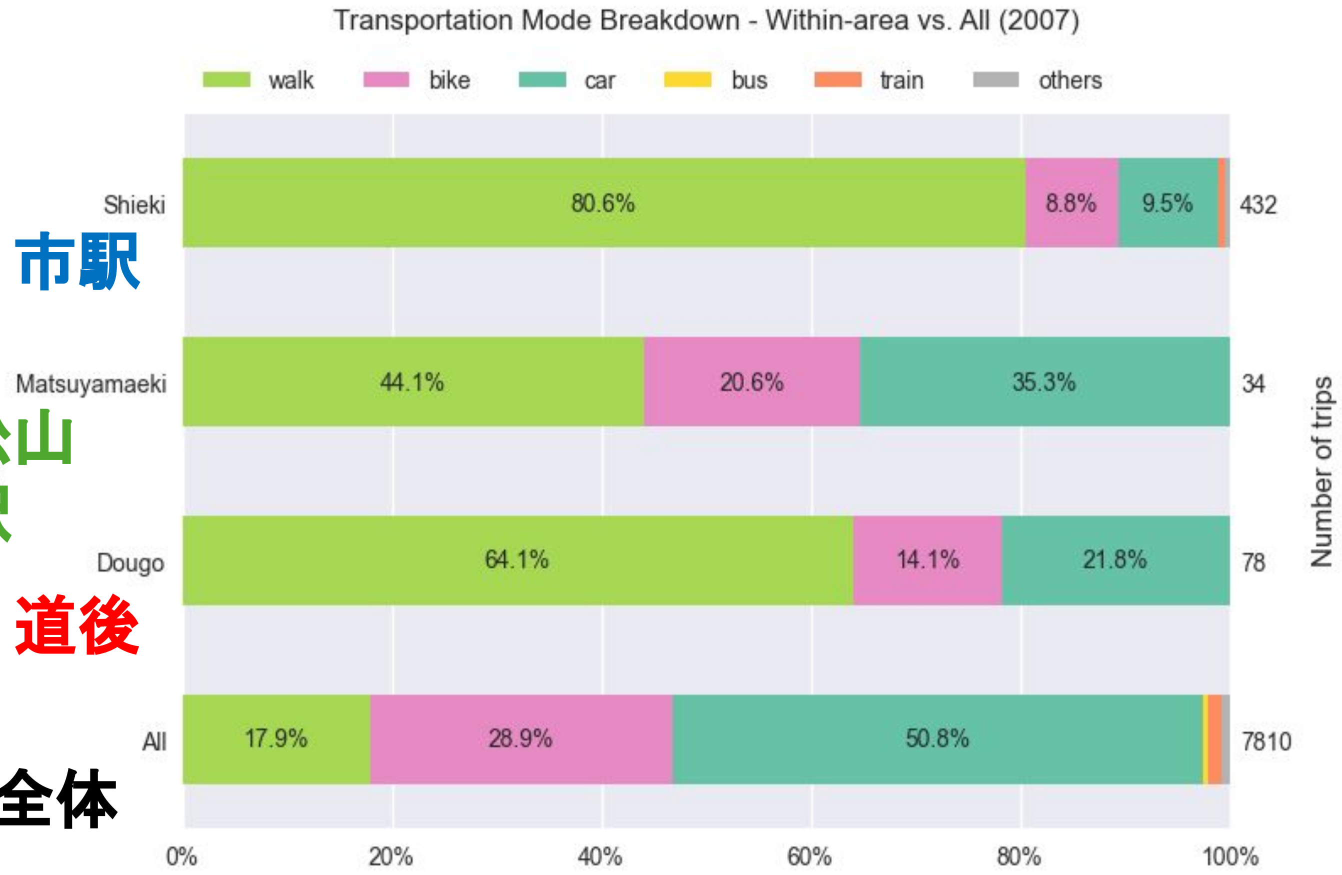
・域内移動の交通手段選択モデル
・歩行者空間の整備が徒歩の選択確率に与える影響を分析
・パラメータ候補：歩行者空間整備距離、移動時間、来訪交通手段、エリアの印象



道後

松山駅

市駅



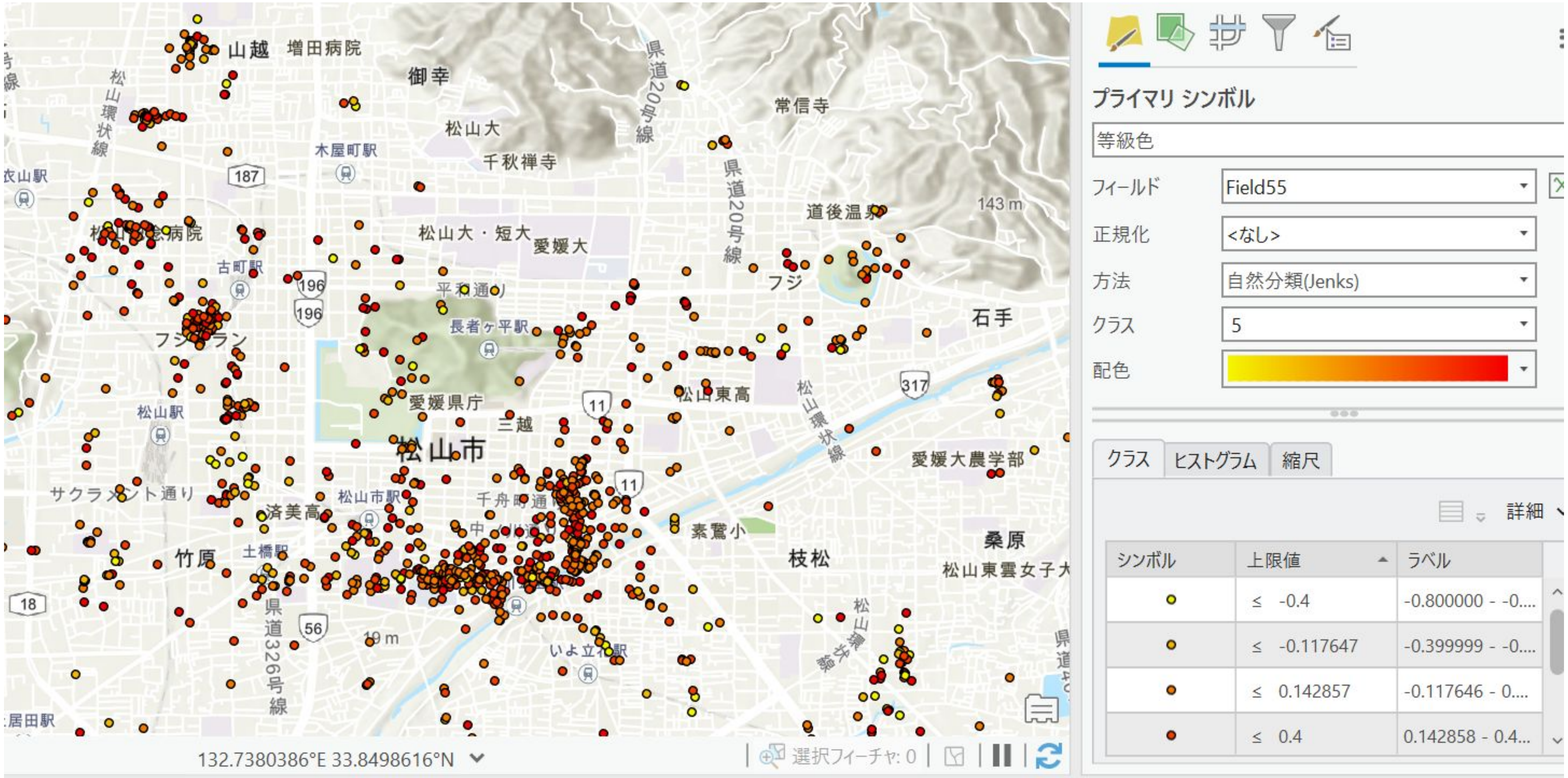
市駅

松山駅

道後

データ全体

EntryのコメントをMecabで形態素分析を行い、単語ごとにネガティブ/ポジティブ(-1~+1)の加点することで、文章の評価を行った。単語の評価については、(小林, 2005)・(東山, 2008) を参考に辞書を制作した。
例 "ツタヤにてCDをレンタルしました。ココは古めのタイトルが充実してるので、昔の曲を聴きたい時、助かります。"
→0.667 positive ”
車で出かけるのもおっくうで近所のスーパーへ。ABCから南へ出る四つ角はみとうしも悪く、暗くなると特に危ない。"→-0.8 negative



前回のスライド：巡回セールスマン問題

決められた地点をすべて1度ずつ訪れて元の地点に戻ってくるための最短経路を探す問題。

一般に、N個の地点だと　$(N-1)(N-2) \times \cdots \times 2 \times 1 = (N-1)!$　通りになる。

巡回セールスマン問題は、**NP困難問題**と呼ばれる難しい問題のクラスに属する。