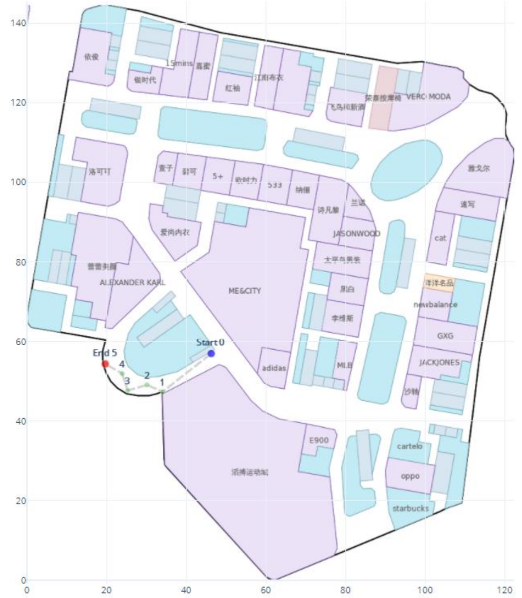
赛题背景

基于试验员在大楼中的位置信息和其手机中传感器信号数据（如wifi强度、wifi基站ID、磁场强度），使用深度学习方法建立模型，达到当给定任意手机传感器数据时，即可定位手机在大楼中位置信息的目的。

https://www.kaggle.com/c/indoor-location-navigation



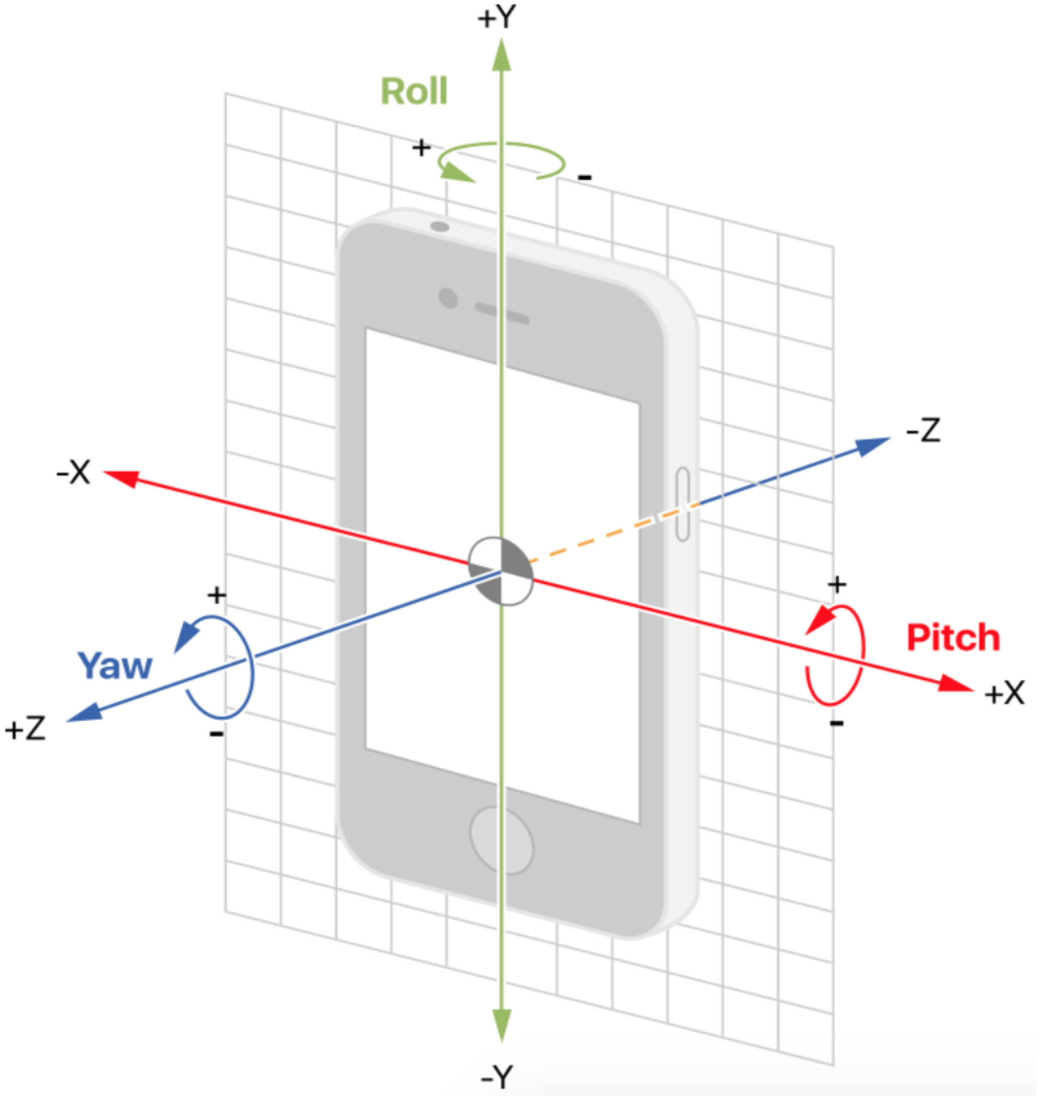
数据概览

Time	Data Type	Value			
1578462618392	TYPE_WAYPOINT	196.418	117.849		
	Location surveyor labeled on the map	Coordinate x (meter)	Coordiante y (meter)		
1578462618392	TYPE_ACCELEROMETER	-1.7086	-0.2748	16.6572	2
	Android Sensor.TYPE_ACCELEROMETER	X axis	Y axis	Z axis	accuracy
1578462618392	TYPE_GYROSCOPE	-0.3022	0.27733	0.10754	3
	Android Sensor.TYPE_GYROSCOPE	X axis	Y axis	Z axis	accuracy
1578462618392	TYPE_MAGNETIC_FIELD	20.1813	16.2094	-32.22	3
	Android Sensor.TYPE_MAGNETIC_FIELD	X axis	Y axis	Z axis	accuracy
1578462618392	TYPE_ROTATION_VECTOR	-0.0086	0.05137	0.3625	3
	Android Sensor.TYPE_ROTATION_VECTOR	X axis	Y axis	Z axis	accuracy

要预测的目标

数据概览

150
100
50
0
奈洛达舞蹈
左庭右院
The ONE智能音乐教室
小鬼当佳
非开放区域
辅助面
七彩轮滑
星控大师美术
伴玩涯趣体验店
韦哲机器人
非开放区域
中空
休息区
吉旺虾佬
斗牛士牛排餐厅
汤姆熊欢乐世界
空铺
小智慧卤肉饭
林东家炸酱面
云海肴·云南菜
爱茜茜里
塔哈尔
西贝莜面村
小辉哥火锅
6号包厢
望湘园
辣些鱼
百合福自助餐厅
老头儿油爆虾
Start Point: 0
End Point
元气寿司
小龙坎老火锅
zippo



+Y
Roll
+
-
-Z
-X
+
+
Yaw
Pitch
+X
+Z
-
-
-Y

数据概览

Time	Data Type	Value						
1578462618392	TYPE_ACCELEROMETER_UNCALIBRATED	-1.7086	-0.2748	16.6572	0	0	0	3
	Android Sensor.TYPE_ACCELEROMETER_UNCALIBRATED	X axis	Y axis	Z axis	X axis	Y axis	Z axis	accuracy
1578462618392	TYPE_GYROSCOPE_UNCALIBRATED	-0.4233	0.20203	0.09624	4.2E-4	3.20E-04	4.12E-04	3
	Android Sensor.TYPE_GYROSCOPE_UNCALIBRATED	X axis	Y axis	Z axis	X axis	Y axis	Z axis	accuracy
1578462618392	TYPE_MAGNETIC_FIELD_UNCALIBRATED	-29.831	-26.363	-300.3	-50.012	-42.572	-268.08	3
	Android Sensor.TYPE_MAGNETIC_FIELD_UNCALIBRATED	X axis	Y axis	Z axis	X axis	Y axis	Z axis	accuracy

数据概览

Time	Data Type	Value							
1.6E+12	TYPE_WIFI	intime_free	0e:74:9c:a7:b2:e4	-43	5805	1.6E+12			
	Wi-Fi data	ssid	bssid	RSSI	frequency	last seen timestamp			
1.6E+12	TYPE_BEACON	FDA50693-A4E2-4FB1-AFCF-C6EB07647825	10073	61418	-65	-82	5.50634	6B:11:4C:D1:29:F2	1.6E+12
	iBeacon data	UUID	MajorID	MinorID	Tx Power	RSSI	Distance	MAC Address	same with Unix time, padding data

BSSID:
无线路由器的MAC地址（唯一）
SSID:
手机上搜到的wifi名字（不唯一）
RSSI:
信号强度（负值，越大越强）

Ibeacon:
蓝牙定位技术
UUID:唯一识别码

评价体系

评价指标：mean position error

Submissions are evaluated on the `mean position error` as defined as:

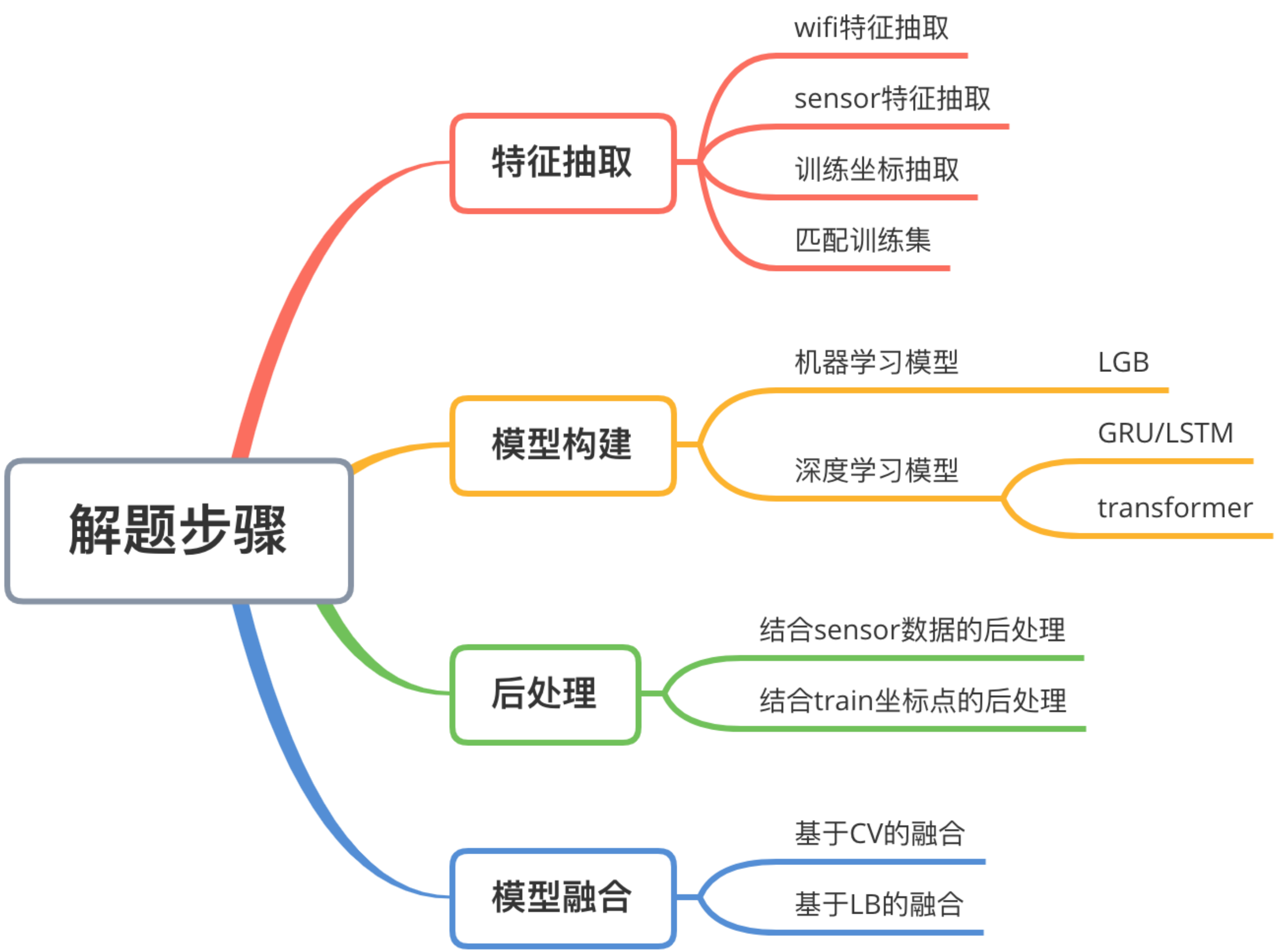
$$\text{mean position error} = \frac{1}{N}\sum_{i=1}^{N}\left(\sqrt{(\hat{x}_i - x_i)^2 + (\hat{y}_i - y_i)^2} + p \cdot |\hat{f}_i - f_i|\right)$$

where:

- N is the number of rows in the test set
- $\hat{x}_i, \hat{y}_i$ are the predicted locations for a given test row
- x_i, y_i are the ground truth locations for a given test row
- p is the floor penalty, set at 15
- $\hat{f}_i, f_i$ are the predicted and ground truth integer floor level for a given test row

```
site_path_timestamp,floor,x,y
5a0546857ecc773753327266_046cfa46be49fc10834815c6_1578474564146,0,15.0,55.0
5a0546857ecc773753327266_046cfa46be49fc10834815c6_1578474573154,0,25.0,65.0
5a0546857ecc773753327266_046cfa46be49fc10834815c6_1578474579463,0,35.0,75.0
etc.
```

思路分析：回归+分类



解题步骤
特征抽取
wifi特征抽取
sensor特征抽取
训练坐标抽取
匹配训练集
模型构建
机器学习模型
LGB
深度学习模型
GRU/LSTM
transformer
后处理
结合sensor数据的后处理
结合train坐标点的后处理
模型融合
基于CV的融合
基于LB的融合

特征抽取：从log文件中抽取关键数据

```
#	startTime:1573893345497
#	SiteID:5dc8cea7659e181adb076a3f	SiteName:龙湖杭州滨江天街	FloorId:5dc8cea7659e181adb076a4d	FloorName:F7
#	Brand:OPPO	Model:PBCM10	AndroidName:8.1.0	APILevel:27
#	type:1	name:BMI160 Accelerometer	version:2062600	vendor:BOSCH	resolution:0.0023956299	power:0.18	maximumRange:39.22661
#	type:4	name:BMI160 Gyroscope	version:2062600	vendor:BOSCH	resolution:0.0010681152	power:0.9	maximumRange:34.906586
#	type:2	name:AK09911 Magnetometer	version:1	vendor:AKM	resolution:0.5996704	power:2.4	maximumRange:4911.9995
#	type:35	name:BMI160 Accelerometer Uncalibrated	version:2062600	vendor:BOSCH	resolution:0.0023956299	power:0.18	maximumRange:39.22661
#	type:16	name:BMI160 Gyroscope Uncalibrated	version:2062600	vendor:BOSCH	resolution:0.0010681152	power:0.9	maximumRange:34.906586
#	type:14	name:AK09911 Magnetometer Uncalibrated	version:1	vendor:AKM	resolution:0.5996704	power:2.4	maximumRange:4911.9995
#	VersionName:v20191105-nightly-16-gcd7805b	VersionCode:403
1573893345513	TYPE_WAYPOINT	213.38832	148.14653
1573893345640	TYPE_ACCELEROMETER	-2.2906494	0.13172913	14.326675	2
1573893345640	TYPE_MAGNETIC_FIELD	26.307678	1.8371582	-32.559204	3
1573893345640	TYPE_GYROSCOPE	0.22261047	-0.31906128	-0.25778198	3
1573893345640	TYPE_ROTATION_VECTOR	-0.014648812	0.051296107	0.65353626	3
1573893345640	TYPE_MAGNETIC_FIELD_UNCALIBRATED	-26.184082	-17.34314	-388.78174	-52.49176	-19.180298	-356.22253	3
1573893345640	TYPE_GYROSCOPE_UNCALIBRATED	0.31628418	-0.30941772	-0.15859985	0.0025939941	0.0016479492	-9.460449E-4	3
1573893345640	TYPE_ACCELEROMETER_UNCALIBRATED	-2.4133453	0.4615326	15.120956	0.0	0.0	0.0	3
1573893345660	TYPE_ACCELEROMETER	-1.9428864	-0.5488281	13.538391	2
1573893345660	TYPE_MAGNETIC_FIELD	24.92981	3.2241821	-31.887817	3
1573893345660	TYPE_GYROSCOPE	0.36535645	-0.2498169	-0.078826904	3
1573893345660	TYPE_ROTATION_VECTOR	-0.01913079	0.051839676	0.6580919	3
1573893345660	TYPE_MAGNETIC_FIELD_UNCALIBRATED	-27.56195	-15.956116	-388.11035	-52.49176	-19.180298	-356.22253	3
1573893345660	TYPE_GYROSCOPE_UNCALIBRATED	0.40629578	-0.16134644	-0.01852417	0.0025939941	0.0016479492	-9.460449E-4	3
1573893345660	TYPE_ACCELEROMETER_UNCALIBRATED	-2.1092834	-0.20585632	13.744293	0.0	0.0	0.0	3
1573893345680	TYPE_ACCELEROMETER	-1.4963684	-1.1976471	13.055954	2
1573893345680	TYPE_MAGNETIC_FIELD	24.92981	1.8371582	-31.887817	3
1573893345680	TYPE_GYROSCOPE	0.4489746	-0.11399841	0.026641846	3
1573893345680	TYPE_ROTATION_VECTOR	-0.02361821	0.04952617	0.66658795	3
1573893345680	TYPE_MAGNETIC_FIELD_UNCALIBRATED	-28.251648	-14.569092	-387.4405	-52.49176	-19.180298	-356.22253	3
1573893345680	TYPE_GYROSCOPE_UNCALIBRATED	0.51123047	-0.11553955	0.0491333	0.0025939941	0.0016479492	-9.460449E-4	3
```

坐标数据

	ts_waypoint	x	y
0	1578462618392	230.03738	153.49635
1	1578462628512	231.40290	158.41515
2	1578462638947	232.46200	164.41673
3	1578462649660	233.94418	171.41417
4	1578463966691	198.36833	163.52063

Wifi数据

	timestamp	ssid	bssid	rssi	last_timestamp
0	1578462618826	63159	162932	-46	1578462603277
1	1578462618826	32835	65513	-49	1578462618272
2	1578462618826	62583	41416	-49	1578462618268
3	1578462618826	52951	213743	-49	1578462618270
4	1578462618826	53216	159807	-49	1578462618271

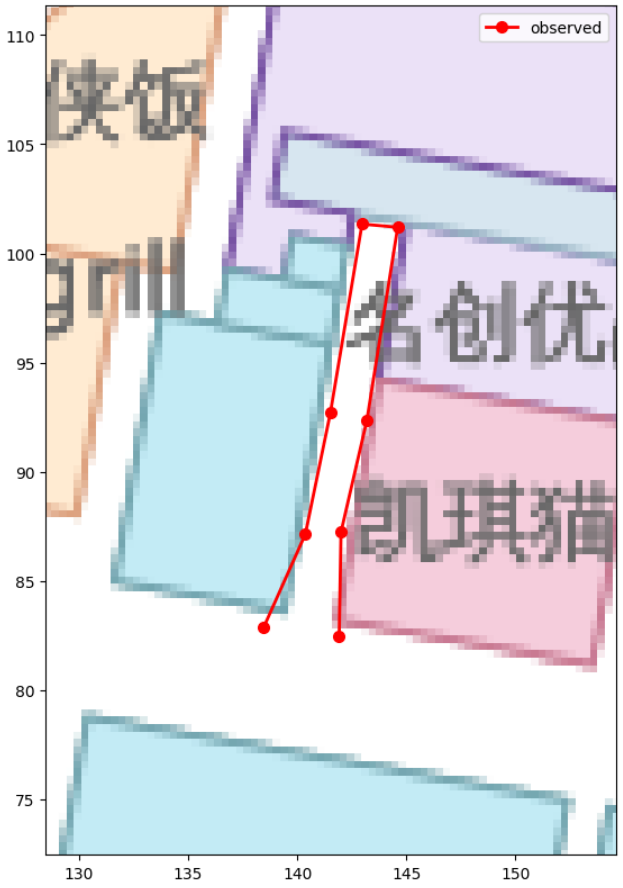
Sensor数据

	ts_sensor	x_acce	y_acce	z_acce	x_magne	y_magne	z_magne
0	1578462618653	0.023697	4.450943	9.055649	-0.037537	0.075256	0.030579
1	1578462618673	0.050629	4.552109	9.074799	-0.043411	-0.005722	0.009796
2	1578462618693	0.001556	4.462326	9.131668	-0.040741	-0.036072	-0.005127
3	1578462618713	0.055420	4.552704	8.652237	0.001877	-0.097336	-0.014709
4	1578462618733	-0.029572	4.634110	8.662399	0.017853	-0.035538	-0.030685

特征抽取：构建训练集

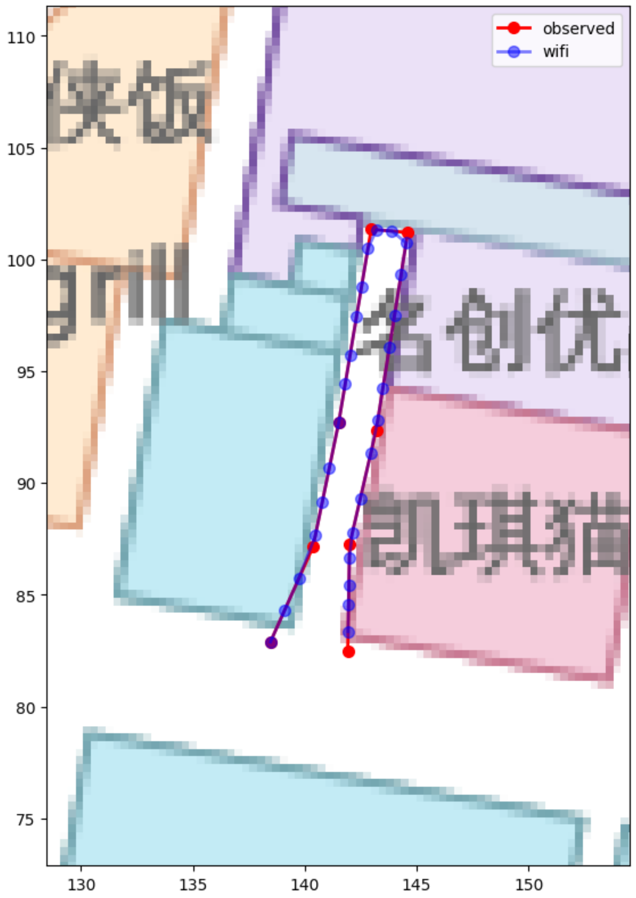
最近距离法

以wifi的timestamp为标杆，选择最近的时间点的sensor和坐标数据，构建训练集。



线性插值法

以wifi的timestamp为标杆，使用线性插值方法，结合sensor和坐标数据，计算wifi的timestamp对应的sensor和坐标值。



模型构建：损失函数

Floor预测：构建多分类模型，损失函数使用交叉熵   tf.keras.losses.CategoricalCrossentropy

坐标预测：构建回归模型，损失函数使用MSE   tf.keras.losses.MSE

Floor+坐标预测：自定义损失函数

```
model.compile(optimizer=tf.optimizers.Adam(lr=0.005),
              loss={'output_x': root_mean_squared_error,
                    'output_y': root_mean_squared_error,
                    'output_f': 'categorical_crossentropy'},
              loss_weights={'output_x': 0.5, 'output_y': 0.5, 'output_f': 15},
              metrics={'output_x': metrics.RootMeanSquaredError(),
                       'output_y': metrics.RootMeanSquaredError(),
                       'output_f': metrics.CategoricalAccuracy()})
```

模型训练：模型架构

LSTM/GRU模型

Wifi

Sensor

Floor

Site

```
inputs = L.Input(shape=(seq_len, 3))
input_time = L.Input(shape = (4+12,))
input_site = L.Input(shape = (1,))

categorical_fea1 = inputs[:, :, :1]
categorical_fea2 = inputs[:, :, 1:2]
numerical_fea = inputs[:, :, 2:]

embed = L.Embedding(input_dim=sid_size, output_dim=embed_dim)(categorical_fea1)
reshaped = tf.reshape(embed, shape=(-1, embed.shape[1],  embed.shape[2] * embed.shape[3]))
reshaped = L.SpatialDropout1D(sp_dropout)(reshaped)
embed2 = L.Embedding(input_dim=bssid_size, output_dim=embed_dim)(categorical_fea2)
reshaped2 = tf.reshape(embed2, shape=(-1, embed2.shape[1],  embed2.shape[2] * embed2.shape[3]))
reshaped2 = L.SpatialDropout1D(sp_dropout)(reshaped2)
hidden = L.concatenate([reshaped, reshaped2, numerical_fea], axis=2)

for x in range(n_layers):
    hidden = gru_layer(hidden_dim, dropout)(hidden)

truncated = hidden[:, :pred_len]
truncated = L.Flatten()(truncated)
embed_site = L.Embedding(input_dim=site_size, output_dim=1)(input_site)
embed_site = L.Flatten()(embed_site)
truncated = L.concatenate([truncated, input_time,embed_site], axis=1)
out = L.Dense(2, activation='linear')(truncated)

model = tf.keras.Model(inputs=[inputs,input_time,input_site], outputs=out)
```

后处理：结合sensor坐标点

To combine machine learning (wifi features) predictions with sensor data (acceleration, attitude heading), I defined cost function as follows,

$$L(X_{1:N}) = \sum_{i=1}^{N} \alpha_i \|X_i - \hat{X}_i\|^2 + \sum_{i=1}^{N-1} \beta_i \|(X_{i+1} - X_i) - \Delta\hat{X}_i\|^2$$

where $\hat{X}_i$ is absolute position predicted by machine learning and $\Delta\hat{X}_i$ is relative position predicted by sensor data.

$$(X - \hat{X})^T A (X - \hat{X}) + (DX - \Delta\hat{X})^T B (DX - \Delta\hat{X})$$

$$A = \begin{pmatrix} \alpha_1 & 0 & 0 \\ 0 & \ddots & 0 \\ 0 & 0 & \alpha_n \end{pmatrix},$$

$$B = \begin{pmatrix} \beta_1 & 0 & 0 \\ 0 & \ddots & 0 \\ 0 & 0 & \beta_{n-1} \end{pmatrix},$$

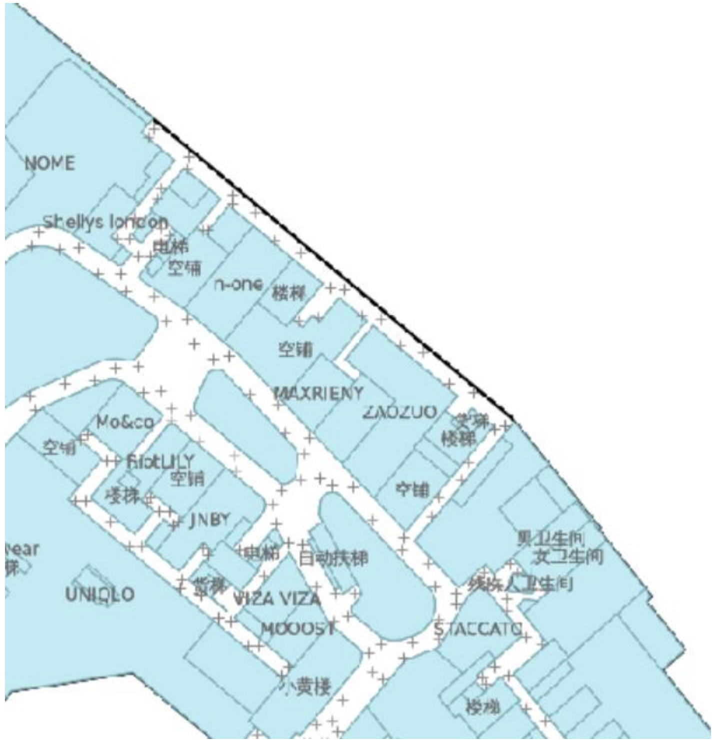
$$D = \begin{pmatrix} -1 & 1 & 0 & 0 \\ 0 & \ddots & \ddots & 0 \\ 0 & 0 & -1 & 1 \end{pmatrix},$$

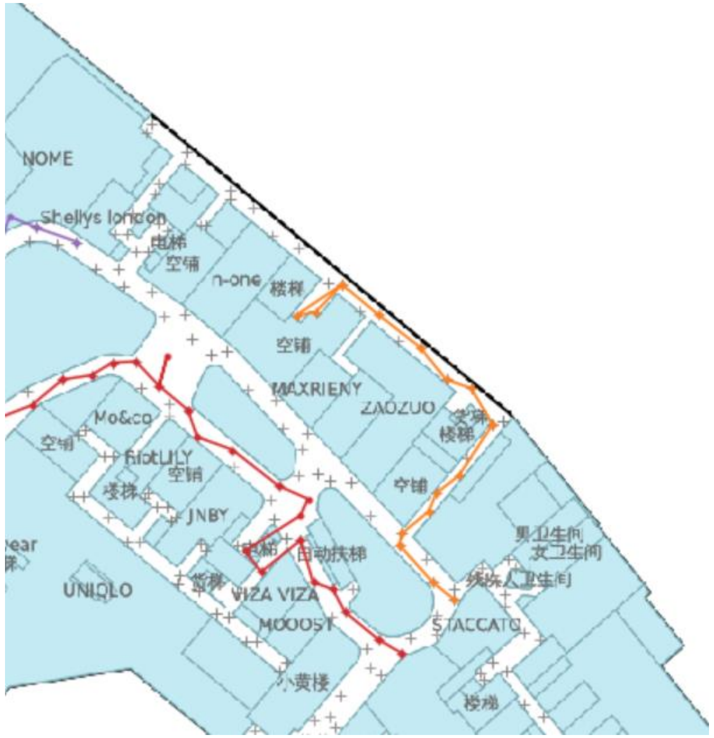
$$(A + A^T)(X - \hat{X}) + D^T(B + B^T)(DX - \Delta\hat{X}) = 0.$$

$$(A + D^T B D)X = A\hat{X} + D^T B \Delta\hat{X},$$

后处理：结合train坐标点

将预测的点坐标调整到最近的train的路径点





模型结果

将各种模型融合后处理，各模型的表现如下：

模型	public LB	private LB
WIFI GRU模型	6.4x	6.8x
WIFI+sensor GRU模型	6.2x	6.6x
WIFI LSTM模型	6.3x	6.7x
WIFI+sensor LSTM模型	6.1x	6.5x
模型融合	5.7x	6.2x
基于sensor的后处理	4.1x	4.5x
基于训练坐标点的后处理	4.0x	4.4x
基于sensor的后处理again	3.9x	4.3x
基于训练坐标点的后处理again	3.8x	4.2x

模型融合后的结果即可得到top3%的成绩。