
2022 Inha AI Challenge

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 Abstract

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1. Abstract



python==3.7.13
pandas==1.3.5
numpy==1.21.5
torch==1.12.0
sklearn==1.0.2



PyTorch



pandas



NumPy

1. Abstract

목표 : 134개 터빈의 2일 동안의 Patv 값 예측

TurbID - 발전기 ID

Day - 날짜

Tmstamp - 시간

Wspd - 풍속

Wdir - 풍이 터빈을 보는 각도와 실제 바람 방향 각도 차이

Etmp - 외부

ltmp - 내부 온도

Ndir - 터빈이 바라보는 방향 각도

Pab - 터빈 당 3개의 날이 있으며 각각의 각도가 다름

Prtv - 무효전력 : 에너지를 필요로 하지 않는 전력

Patv - 유효전력 : 실제로 터빈을 돌리는 일을 하는 전력

GRU + CNN

	A	B	C	D
1	TurbID	x	y	
2	1	3349,852	5939,232	
3	2	3351,002	6416,647	
4	3	3314,78	6892,184	
5	4	3352,094	7366,142	
6	5	3355,342	7841,202	
7	6	3329,428	8340,798	
8	7	3360,547	8816,238	
9	8	3360,299	9265,014	
10	9	3359,942	9681,015	
11	10	3351,002	10111,015	
12	11	3351,002	10641,015	
13	12	3351,002	11171,015	
14	13	3351,002	11701,015	
15	14	3328,78	719,0482	
16	15	3329,759	1194,288	
17	16	3333,904	1658,257	
18	17	3334,256	2140,554	
19	18	3336,848	2615,588	
20	19	3338,886	3090,449	
21	20	3361,034	3566,919	
22	21	3249,022	4043,586	

목차

 Abstract

 **Feature**

 Prepare

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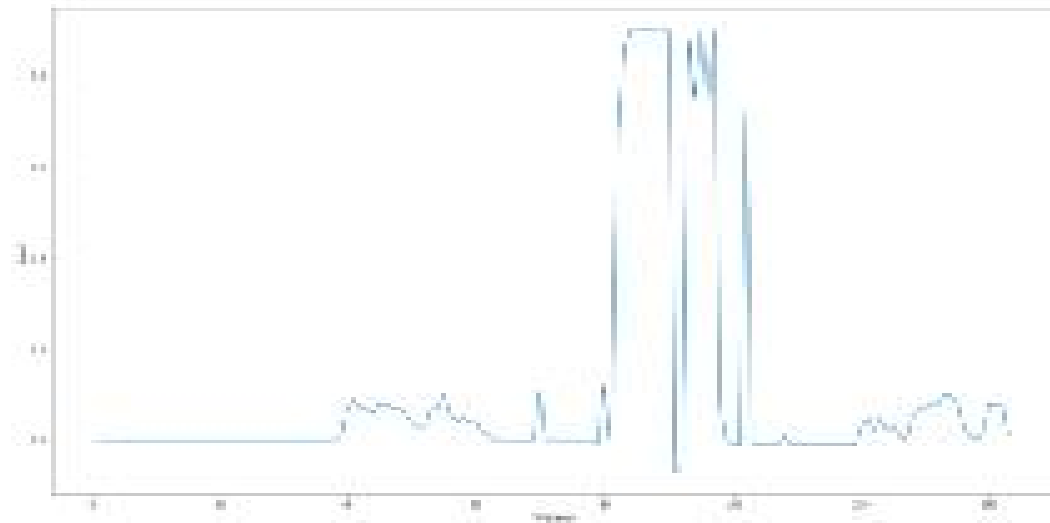
 Q&A

2. Feature

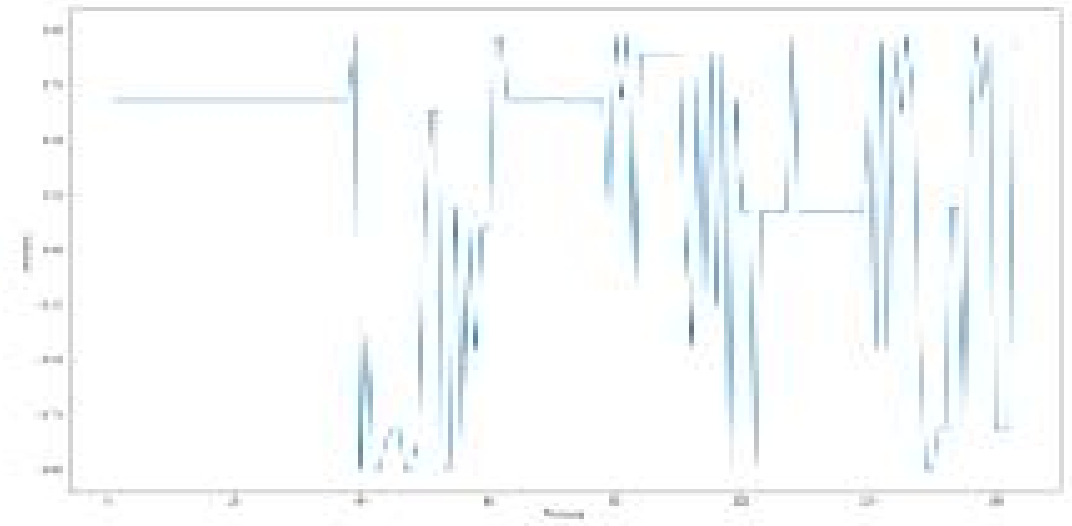


(TurbID == 1 & Day == 1)

pab1



$\sin(pab1)$



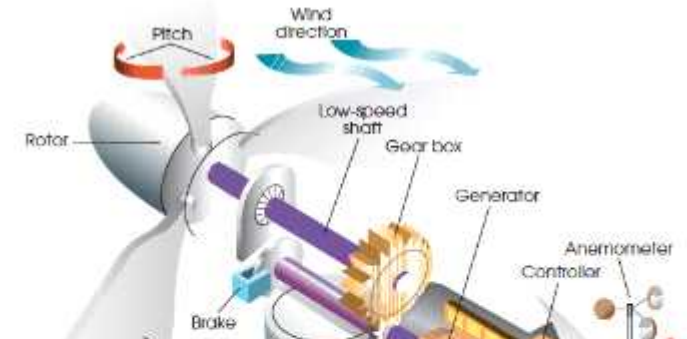
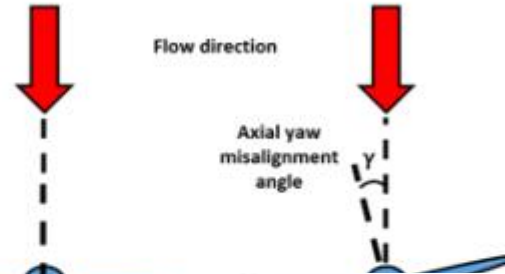
2. Feature



2. Feature

$$\dot{P} = \frac{1}{2} \times \rho \times A \times (V \times \cos \gamma)^3$$

Patv (Pointed to by a red arrow)
 Wspd (Pointed to by a blue arrow)



풍력발전의 원리 / YTN 사이언스

조회 수 45,510 | 2015.1.15



풍력발전의 원리 / YTN 사이언스

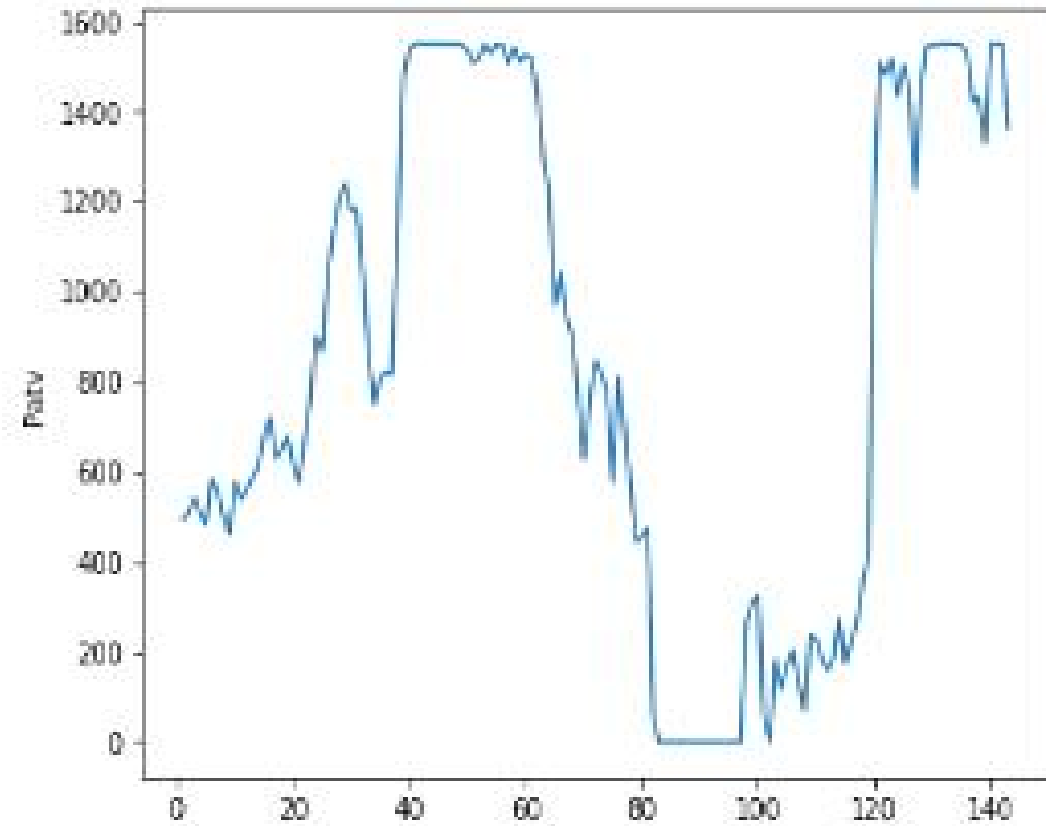
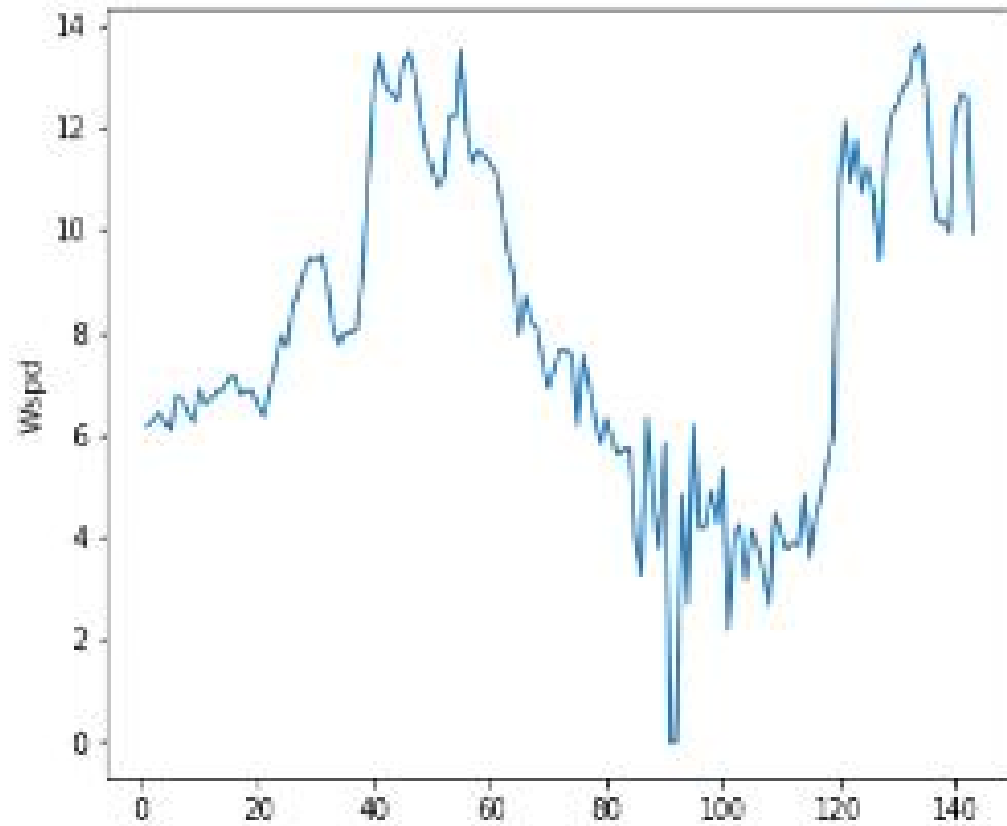
조회 수 45,510 | 2015.1.15



2. Feature

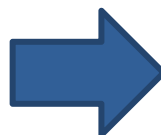
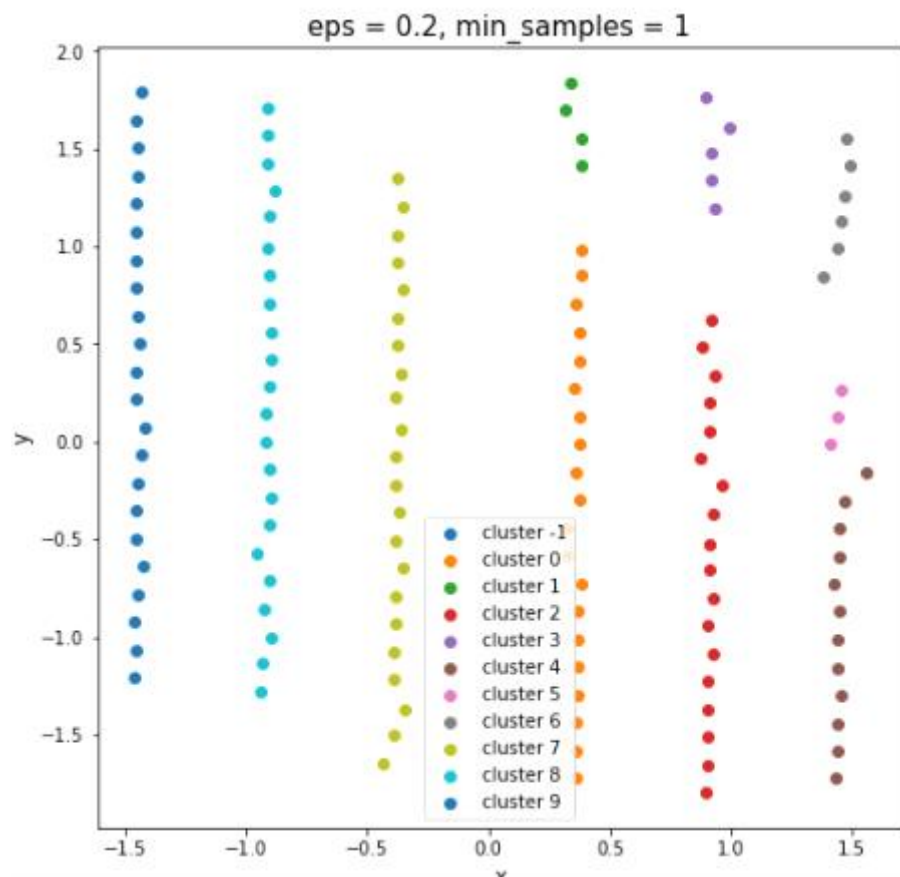
(TurbID == 1 & Day == 1)

Wspd 와 Patv 비교



2. Feature

공간정보 .. ?



```
1 cluster_df.iloc[[1,10,20,30,40,50,60,70], :]
```

	c10	c11	c12	c13	c14	c15	c16	c17	c18	c19	TurbID
1	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	2
10	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	11
20	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	21
30	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	31
40	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	41
50	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	51
60	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	61
70	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	71

2. Feature

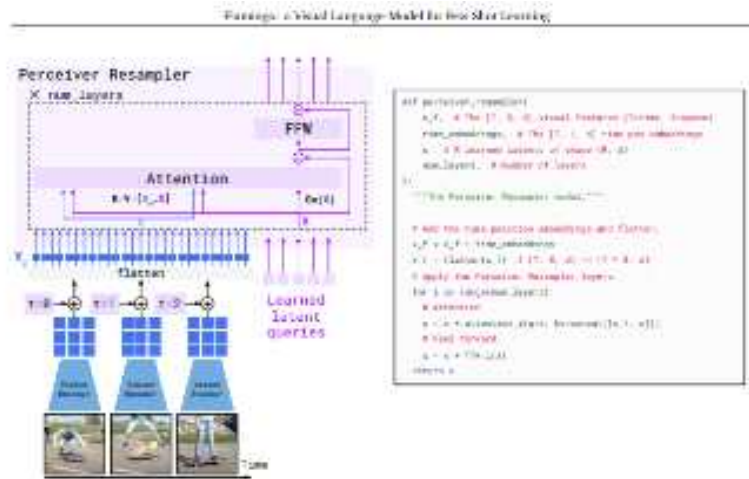


Figure 4 | The Perceiver Resampler module maps a variable size grid of spatio-temporal visual features coming out of the Vision Encoder to a fixed number of output tokens (five in the figure), independently of the input image resolution or the number of input video frames. This transformer has a set of learned latent vectors as queries, and the keys and values are a concatenation of the spatio-temporal visual features with the learned latent vectors. More details can be found in Section 3.1.1.

architecture in Figure 3. It takes as input a variable number of image or video features from the vision encoder and produces a fixed number of visual outputs as illustrated in Figure 4 (hence the name Resampler). The motivation for re-sampling the visual input to a fixed and small number (in practice 64) of outputs is to significantly reduce the computational complexity of vision-text cross attention, particularly important when dealing with multiple long videos. In similar spirit to Perceiver (Jaegle et al., 2021) and DETR (Carion et al., 2020), we learn a predefined number of latent input queries. These latent queries are fed to a transformer stack and cross attend to the flattened visual features X_V . These visual features are obtained by first adding a learnt temporal position encoding to each spatial grid of features corresponding to a given frame of the video (an image being considered as a single-frame video). Note that we only use temporal encodings and not spatial grid position encodings; we did not observe improvements from the latter, potentially because CNNs implicitly encode space information channel-wise (Islam et al., 2021). The visual features are then flattened and concatenated as illustrated in Figure 4. The number of output tokens of the Resampler is thus equal to the number of learnt latent queries. Unlike in DETR and Perceiver, the keys and values computed from the learnt latents are concatenated to the keys and values obtained from X_V , which we found to perform slightly better. We show later in the ablation studies (Section 4.4), that using such a vision language resampler module outperforms a plain transformer and an MLP. More architectural details are provided in Table 13.

3.1.2. Conditioning a frozen language model on visual representations

As illustrated in Figure 5, text generation is performed by a Transformer decoder, conditioned on the visual representations X produced by the Perceiver Resampler. We build this model by interleaving

because CNNs implicitly encode space information channel-wise.
(CNN은 암묵적으로 공간 정보를 채널별로 인코딩하기 때문이다.)

CNN의 활용

2. Feature

하나의 터빈에 대하여 **거리가 가까운 121개 터빈**의 Patv값을 입력

11



256x256 이미지 예시



Patv값	Patv값	Patv값					
					Patv값	Patv값	Patv값

11

11x11 이미지 예시

목차

 Abstract

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3. Prepare

```
1 input_len = 144 # id 한 개당 하루에 생성되는 row의 갯수 (24hour / 10minute = 144)
2
3 for turbid in range(134): # 터빈 마다의 갯수
4     # print(turbid)
5     full_dict = collections.defaultdict(list)
6     turb_data = df[df['TurbID']==turbid+1].reset_index(drop=True)
7     ls = list(turb_data['Patv'])
8     for i in range(0, len(ls)-288-input_len): # range(0, ) # 288 (id 당 예측해야 하는 patv 갯수 2일 -> 144 * 2)
9         if i % 10000 == 1: print(i)
10        # i 가 0 이면 %spd의 처음 시작 1일 0시 00분 부터 1일 23시 50분까지의 %spd 리스트 추가
11        full_dict['%spd_seq'].append(list(turb_data['%spd'])[i:i+input_len])
12        full_dict['Patv_seq'].append(list(turb_data['Patv'])[i:i+input_len])
13        full_dict['Etap_seq'].append(list(turb_data['Etap'])[i:i+input_len])
14        full_dict['Itap_seq'].append(list(turb_data['Itap'])[i:i+input_len])
15        full_dict['Pabl_seq'].append(list(turb_data['Pabl'])[i:i+input_len])
16
17        full_dict['target'].append(list(turb_data['Patv'])[i+input_len:i+input_len+288])
18        # i 가 0이면 [144: 144 + 288] (288개의 patv 값 저장)
19    df_his = pd.DataFrame(full_dict)
20    df_his.to_csv('turbine_data'+str(turbid+1)+'.csv', index=False)
21
```

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 - turbine_data134.csv
 - train_data42.csv
 - dist_dict.pickle

3. Prepare

1 df.head(10)

	TurbID	Day	Tmstamp	Wspd	Etmp	Itmp	Pabl	Patv
0	1	1	00:00	0.00	0.00	0.00	0.0	0.00
1	1	1	00:10	6.17	30.73	41.80	1.0	494.66
2	1	1	00:20	6.27	30.60	41.63	1.0	509.76
3	1	1	00:30	6.42	30.52	41.52	1.0	542.53
4	1	1	00:40	6.25	30.49	41.38	1.0	509.36
5	1	1	00:50	6.10	30.47	41.22	1.0	482.21
6	1	1	01:00	6.77	30.31	41.19	1.0	584.75
7	1	1	01:10	6.70	30.24	41.00	1.0	557.98
8	1	1	01:20	6.44	30.13	40.91	1.0	503.94
9	1	1	01:30	6.25	29.97	40.72	1.0	463.37

	Wspd_seq	Patv_seq	Etmp_seq	Itmp_seq	Pabl_seq	target
0	[0.0, 6.17, 6.27, 6.42, 6.25, 6.1, 6.77, 6.7, ...]	[0.0, 494.66, 509.76, 542.53, 509.36, 482.21, ...]	[0.0, 30.73, 30.6, 30.52, 30.49, 30.47, 30.31, ...]	[0.0, 41.8, 41.63, 41.52, 41.38, 41.22, 41.19, ...]	[0.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, ...]	[1468.21, 718.12, 442.15, 196.04, 234.35, 124.94, ...]
1	[6.17, 6.27, 6.42, 6.25, 6.1, 6.77, 6.7, 6.44, ...]	[494.66, 509.76, 542.53, 509.36, 482.21, 584.75, ...]	[30.73, 30.6, 30.52, 30.49, 30.47, 30.31, 30.2, ...]	[41.8, 41.63, 41.52, 41.38, 41.22, 41.19, 41.0, ...]	[1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, ...]	[718.12, 442.15, 196.04, 234.35, 124.94, 179.06, ...]
2	[6.27, 6.42, 6.25, 6.1, 6.77, 6.7, 6.44, 6.25, ...]	[509.76, 542.53, 509.36, 482.21, 584.75, 557.98, ...]	[30.6, 30.52, 30.49, 30.47, 30.31, 30.24, 30.1, ...]	[41.63, 41.52, 41.38, 41.22, 41.19, 41.0, 40.9, ...]	[1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, ...]	[442.15, 196.04, 234.35, 124.94, 179.06, 253.25, ...]
3	[6.42, 6.25, 6.1, 6.77, 6.7, 6.44, 6.25, 6.87, ...]	[542.53, 509.36, 482.21, 584.75, 557.98, 503.94, ...]	[30.52, 30.49, 30.47, 30.31, 30.24, 30.13, 29, ...]	[41.52, 41.38, 41.22, 41.19, 41.0, 40.91, 40.7, ...]	[1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, ...]	[196.04, 234.35, 124.94, 179.06, 253.25, 347.0, ...]
4	[6.25, 6.1, 6.77, 6.7, 6.44, 6.25, 6.87, 6.6, ...]	[509.36, 482.21, 584.75, 557.98, 503.94, 463.37, ...]	[30.49, 30.47, 30.31, 30.24, 30.13, 29.97, 29, ...]	[41.38, 41.22, 41.19, 41.0, 40.91, 40.72, 40.7, ...]	[1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, ...]	[234.35, 124.94, 179.06, 253.25, 347.0, 249.3, ...]

3. Prepare

```
df.iloc[144:144+10,:]
```

	TurbID	Day	Tmstamp	Wspd	Etmp	Itmp	Pab1	Patv
144	1	2	00:00	10.64	28.10	42.17	1.01	1468.21
145	1	2	00:10	7.00	27.87	42.05	1.00	718.12
146	1	2	00:20	5.87	27.38	41.73	0.99	442.15
147	1	2	00:30	4.00	27.13	41.76	0.99	196.04
148	1	2	00:40	4.03	26.99	41.66	0.99	234.35
149	1	2	00:50	3.46	26.80	41.36	0.99	124.94
150	1	2	01:00	3.96	26.52	40.87	0.99	179.06
151	1	2	01:10	4.63	26.25	39.97	0.99	253.25
152	1	2	01:20	5.40	26.01	39.09	0.99	347.00
153	1	2	01:30	4.73	25.84	38.32	0.99	249.30



	Wspd_seq
0	[0.0, 6.17, 6.27, 6.42, 6.25, 6.1, 6.77, 6.7, ...]
1	[6.17, 6.27, 6.42, 6.25, 6.1, 6.77, 6.7, 6.44, ...]
2	[6.27, 6.42, 6.25, 6.1, 6.77, 6.7, 6.44, 6.25, ...]
3	[6.42, 6.25, 6.1, 6.77, 6.7, 6.44, 6.25, 6.87, ...]
4	[6.25, 6.1, 6.77, 6.7, 6.44, 6.25, 6.87, 6.6, ...]

./

README.md

prepare.ipynb

model.ipynb

test.ipynb

data

turbine_data1.csv

turbine_data2.csv

turbine_data134.csv

train_data42.csv

dist_dict.pickle

target

[1468.21, 718.12, 442.15, 196.04, 234.35, 124.94, ...]

[718.12, 442.15, 196.04, 234.35, 124.94, 179.06, ...]

[442.15, 196.04, 234.35, 124.94, 179.06, 253.25, ...]

[196.04, 234.35, 124.94, 179.06, 253.25, 347.00, ...]

[234.35, 124.94, 179.06, 253.25, 347.00, 249.30, ...]

하루(144개)의 Feature list * 5 → 이틀치의(288개) Target list 예측

3. Prepare

```
In [37]: for i in tqdm(range(134)):
df_tmp = pd.read_csv('data/turbine_data'+str(i+1)+'.csv')
df_tmp['index'] = list(range(len(df_tmp)))
df_tmp = df_tmp.sample(frac=0.01, random_state=2)
index_list = list(df_tmp['index'])
df_tmp['TurbID'] = i+1

turb_data = df[df['TurbID']==i+1].reset_index(drop=True)
near_turbs = dist_dict[i+1][:121]
index_new = [x+144-1 for x in index_list]
selected_df = turb_data.loc[index_new]
selected_df = pd.merge(selected_df, df_group, how='left', on=['day', 'TurbID'])
selected_df['Pate_space'] = selected_df['Pate_list'].apply(lambda x: [x[-1] for x in near_turbs])
df_tmp['Pate_space'] = list(selected_df['Pate_space'])

if i==0:
    train = df_tmp.copy()
else:
    train = pd.concat([train, df_tmp])
train = train.reset_index(drop=True)
train = train.sample(frac=1, random_state=2).reset_index(drop=True)

100%|████████████████████████████████████████| 134/134 [03:45<00:00] 0.1 63s/1.1]

In [38]: cols = [x for x in train.columns if 'seq' in x or x=='angle']
for col in cols:
    train[col] = train[col].apply(lambda x: [seq.loads(x)])

train = drop_naonnae(train)
train.to_csv('data/train_data42.csv', index=False)

In [42]: dat42 = pd.read_csv('data/train_data42.csv')
print(dat42)
```

```
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│   ├── turbine_data134.csv
│   └── train_data42.csv
└── dist_dict.pickle
```

3. Prepare

TurbID	Index	Wpd_seq	Patv_seq	Flap_seq	Flap_seq	Patl_seq	Patv_space	target
1	02	[10.45, 9.61, 9.17, 7.06, 8.71, 8.22, 8.08, ...]	[1442.40, 1392.17, 1325.7, 962.02, 5011.58, 99...	[32.73, 32.8, 33.04, 33.27, 33.57, 33.67, ...]	[43.33, 45.42, 45.51, 43.34, 46.39, 46.09, ...]	[1.01, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, ...]	[378.1, 498.75, 505.85, 505.58, 508.71, 580.74, ...]	[593.59, 503.09, 591.57, 444.78, 403.78, 511.5...
1	137	[4.61, 5.7, 4.71, 4.43, 4.25, 3.14, 3.7, 4.57, ...]	[353.25, 347.8, 348.3, 205.14, 254.04, 1431.7, ...]	[33.21, 23.0, 23.64, 25.46, 25.47, 24.95, ...]	[39.97, 39.09, 38.32, 37.88, 41.35, 38.7, ...]	[0.53, 0.59, 0.59, 0.94, 0.99, 1.0, 0.99, ...]	[593.43, 1457.23, 1174.17, 1100.27, 1474.57, 1, ...]	[1548.52, 1545.65, 1549.37, 1408.51, 1511.17, ...]
1	258	[5.04, 3.78, 4.05, 4.4, 3.65, 3.59, 3.11, 2.77, ...]	[121.01, 164.85, 205.14, 240.6, 163.27, 145.6, ...]	[31.54, 31.85, 31.0, 31.75, 31.53, 31.34, 31.1, ...]	[39.06, 39.51, 39.36, 39.75, 39.51, 39.4, 39.3, ...]	[0.99, 0.99, 0.99, 0.99, 0.99, 0.99, 0.99, 0.9, ...]	[1537.3, 1466.75, 1492.27, 1492.34, 1447.55, 1, ...]	[1490.34, 1481.3, 1489.68, 1530.56, 1521.49, 1, ...]
1	393	[11.18, 11.57, 11.75, 11.63, 11.13, 11.73, 10, ...]	[1511.29, 1532.37, 1537.87, 1509.91, 1500.71, ...]	[39.31, 37.27, 39.27, 39.13, 39.41, 39.4, 39.3, ...]	[43.02, 43.03, 42.59, 43.01, 43.03, 43.04, 43, ...]	[1.02, 1.04, 1.05, 1.04, 1.01, 1.04, 1.03, 1.0, ...]	[1443.36, 440.9, 378.32, 445.35, 557.52, 485.14, ...]	[493.32, 474.48, 427.88, 134.98, 393.54, 439.54, ...]
1	467	[11.53, 11.55, 11.77, 11.63, 12.02, 12.54, 12, ...]	[1457.01, 1544.07, 1547.87, 1548.71, 1531.55, ...]	[22.28, 22.2, 22.14, 22.09, 22.03, 22.03, 22.1, ...]	[37.19, 37.09, 37.09, 37.08, 37.05, 36.99, 36, ...]	[1.07, 1.06, 1.07, 1.07, 1.07, 1.09, 1.08, 1.0, ...]	[319.55, 833.64, 800.01, 892.72, 1234.27, 813, ...]	[1432.55, 1209.03, 1197.95, 1084.28, 1090.52, ...]
1	493	[11.89, 12.56, 12.56, 11.27, 11.51, 12.51, 12, ...]	[1510.99, 1528.67, 1504.16, 1510.32, 737.9, 15, ...]	[23.85, 23.94, 23.12, 23.3, 23.64, 23.97, 23.5, ...]	[37.49, 37.41, 37.43, 37.52, 37.56, 38.01, 37, ...]	[1.07, 1.09, 1.08, 1.05, 1.02, 1.06, 1.07, 1.0, ...]	[1.03, 1.03, 1.03, 0.63, 16, 0.3, 0.53, 54, 0.0, ...]	[1543.78, 1503.18, 1493.59, 1517.56, 1511.07, ...]
1	595	[12.23, 12.03, 12.12, 11.58, 11.79, 12.39, 12, ...]	[1542.44, 1547.11, 1534.13, 1545.98, 1527.82, ...]	[24.72, 25.05, 25.42, 25.7, 26.0, 26.58, 25.55, ...]	[38.35, 38.36, 38.32, 39.17, 39.32, 39.33, 40, ...]	[1.07, 1.06, 1.07, 1.08, 1.06, 1.07, 1.08, 1.0, ...]	[1.03, 1.03, 1.03, 0.3, 0.3, 341.60, 154.45, 0.3, 276.08, 0.0, ...]	[1318.48, 1512.33, 1489.15, 1470.04, 1490.43, ...]
1	597	[11.89, 11.09, 12.38, 11.63, 12.53, 12.53, 12, ...]	[1531.31, 1545.88, 1542.25, 1535.57, 1545.12, ...]	[27.25, 27.3, 27.15, 26.13, 26.54, 27.01, 26.1, ...]	[41.04, 41.11, 41.15, 41.98, 41.08, 42.38, 42, ...]	[1.06, 1.08, 1.06, 1.05, 1.08, 1.06, 1.07, 1.0, ...]	[1.03, 1.03, 1.03, 0.03, 0.1, 225.95, 227.03, 0.1, 227.87, 0.0, ...]	[1537.87, 1501.7, 1510.87, 1491.38, 1493.51, 1, ...]
1	592	[8.28, 7.79, 8.83, 9.07, 8.71, 8.99, 9.07, 9.3, ...]	[438.45, 382.05, 1074.40, 1079.95, 1053.42, 10, ...]	[29.97, 29.92, 29.67, 29.7, 29.6, 29.44, 29.3, ...]	[39.3, 39.71, 39.79, 39.77, 39.74, 39.54, 40.0, ...]	[1.09, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, ...]	[553.19, 871.88, 543.72, 775.49, 488.81, 893.0, ...]	[1403.08, 878.75, 1288.2, 1383.93, 1082.90, 873, ...]
1	598	[8.71, 8.89, 9.07, 9.33, 9.25, 8.85, 9.51, 9.1, ...]	[1033.42, 1057.11, 1154.13, 1151.08, 1164.38, ...]	[29.61, 29.44, 29.52, 29.13, 29.90, 29.83, 30, ...]	[39.74, 39.58, 40.08, 40.15, 40.22, 40.52, 40, ...]	[1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, ...]	[1061.57, 1060.06, 1183.40, 1169.64, 1010.8, 1, ...]	[1060.56, 873.89, 754.68, 500.25, 381.34, 474, ...]

거리가 가까운 121개의 터빈의
Patv 값을 feature로 사용

11 by 11 matrix로 만들어
CNN의 이미지로 활용

목차

□ Abstract

□ Feature

□ Prepare

■ **Model**

□ Test

□ Q&A

4. Model(GRU + CNN)

```
class GRU(nn.Module):
    def __init__(self):
        super(GRU, self).__init__()

        self.gru = nn.GRU(input_size=4, hidden_size=48, num_layers=2)
        self.dropout = nn.Dropout(0.05)

        # self.Linear = nn.Linear(48+2, 1, bias_attr=True)
        self.Linear = nn.Linear(48+2, 1)

        self.cnn_layer = nn.Sequential(
            nn.Conv2d(1, 64, kernel_size=3, stride=1, padding=1),
            nn.BatchNorm2d(64),
            nn.GELU(),
            nn.MaxPool2d((3, 3)))

    def forward(self, X, space_data):
        # x = torch.zeros([X.shape[0], 144, X.shape[1]], dtype="float32")
        x = torch.zeros([X.shape[0], 144, X.shape[1]])
        x = x.to(device)

        # x = torch.concat((X.transpose([0, 2, 1]), x), axis=1)
        # print(X.shape)
        # print(x)
        # print(type(x))
        # print(type(X))
        # print(type(x))
        x = torch.concat((torch.transpose(X, 2, 1), x), axis=1)
        # print(1)
        out1, _ = self.gru(x)
        out1 = self.dropout(out1)

        cnn_out = self.cnn_layer(space_data)
        # print(cnn_out.shape)
        cnn_out = torch.reshape(cnn_out, (cnn_out.shape[0], 288, -1))
        # print(cnn_out.shape)
        out2 = self.Linear(torch.concat((out1, cnn_out), 2))

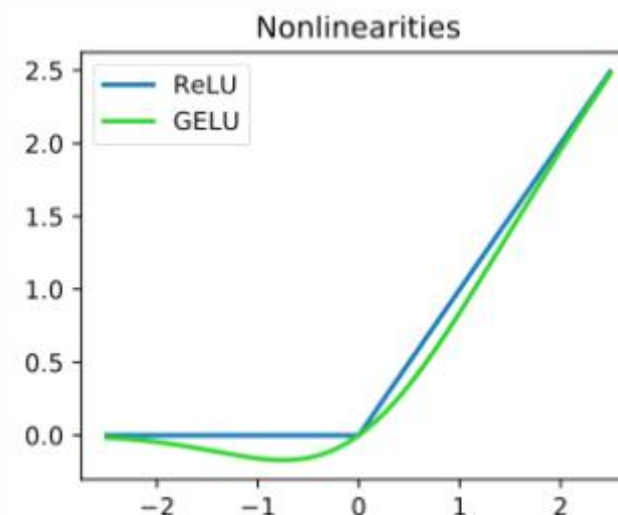
    return out2
```

[하이퍼파라미터]

batch = 16,32,64

lr = 0.0005, 0.0003, 0.0001

optimizer = GELU, RELU



4. Model(GRU + CNN)

Image

```
tensor([[379., 498., 506., 506., 509., 391., 328., 409., 490., 474., 575.],
        [455., -0., 462., 335., 293., -0., 301., 336., 278., -0., 424.],
        [427., 339., -0., 282., 215., 351., -0., -0., 180., -0., -0.],
        [-0., 391., -0., -0., -0., -0., 423., 226., -0., -0., 217.],
        [-0., -0., 350., -0., 135., 180., -0., -0., -0., -0., -0.],
        [-0., -0., 324., 276., -0., -0., 131., 235., -0., -0., -0.],
        [312., -0., -0., -0., 120., 233., -0., -0., 110., -0., 94.],
        [-0., 64., -0., 133., -0., 0., -0., -0., 135., -0., 120.],
        [110., -0., -0., -0., 104., 125., -0., 163., 131., -0., -0.],
        [-0., -0., 244., -0., -0., -0., 129., -0., 79., -0., -0.],
        [42., -0., -0., 257., 111., -0., 2., -0., -0., -0., -0.]])
```

Conv2d



```
1 s2 = torch.reshape(np.round(s1,0),(-1,1,11,11))
```

```
1 conv1 = nn.Conv2d(1, 64, kernel_size=3, stride=1, padding=1)
2 out1 = conv1(s2)
```

```
1 out1.shape
```

```
torch.Size([1, 64, 11, 11])
```

```
1 torch.round(out1[0][0])[:,:]
```

```
tensor([[ 14., -19., -16., 70., 133., 16., -46., 21., 109., -47.,
          143.],
        [-94., -65., -170., -158., -115., -74., -63., -155., -77., -161.,
          -119.],
        [-207., 67., -52., -118., -95., -80., -62., -26., -24., -70.,
          -74.],
        [-164., -154., 38., -37., -109., -111., 22., 53., -22., -44.,
          22.],
        [-11., -221., -26., 100., 41., -15., -133., -31., 30., -6.,
          -50.],
        [ 32., 3., -86., -2., -59., -22., 12., 7., 31., -3.,
          10.],
        [ 16., 23., -103., -89., -15., 30., -17., -112., 9., -9.,
          22.],
        [-69., 6., -14., -16., -44., -28., -33., -39., 34., 9.,
          -9.],
        [ 9., -67., 17., 1., -17., -11., -0., -1., 4., 13.,
          -28.],
        [-21., -35., -39., 16., 34., -34., 0., -41., -33., -3.,
          -0.],
        [ 4., -4., -93., -6., 33., 5., -29., -11., -18., -6.,
          -0.]])
```

Ex) Convolution

0	0	0	0	0	0	0
0	60	113	56	139	85	0
0	71	121	54	144	128	0
0	131	99	70	129	127	0
0	80	57	115	69	136	0
0	104	126	123	95	130	0
0	0	0	0	0	0	0

Kernel		
0	1	0
-1	5	-1
0	-1	0

114	328	26	470	158
51	266	-61	-30	344
403	116	-67	295	240
108	-135	256	-128	364
314	346	279	153	421

4. Model(GRU + CNN)

```
tensor([[ 14., -19., -16., 70., 133., 16., -46., 21., 109., -47.,
         143.],
        [-94., -65., -170., -158., -115., -74., -63., -155., -77., -161.,
        -119.],
        [-207., 67., -52., -118., -95., -80., -62., -26., -24., -70.,
        -74.],
        [-164., -154., 38., -37., -109., -111., 22., 53., -22., -44.,
        22.],
        [-11., -221., -26., 100., 41., -15., -133., -31., 30., -6.,
        -50.],
        [ 32., 3., -86., -2., -59., -22., 12., 7., 31., -3.,
        10.],
        [ 16., 23., -103., -89., -15., 30., -17., -112., 9., -9.,
        22.],
        [-69., 6., -14., -16., -44., -28., -33., -39., 34., 9.,
        -9.],
        [ 9., -67., 17., 1., -17., -11., -0., -1., 4., 13.,
        -28.],
        [-21., -35., -39., 16., 34., -34., 0., -41., -33., -3.,
        -0.],
        [ 4., -4., -93., -6., 33., 5., -29., -11., -18., -6.,
        -0.]], grad_fn=<SliceBackward0>)
```

BatchNormalization



```
1 batch1 = nn.BatchNorm2d(64)
2 out2 = batch1(out1)
3 print(out2.shape)
4 out2[0][0]

torch.Size([1, 64, 11, 11])
tensor([[ 6.6612e-01,  1.3315e-01,  1.8540e-01,  1.5603e+00,  2.5513e+00,
          6.8686e-01, -2.9704e-01,  7.7814e-01,  2.1786e+00, -3.0944e-01,
          2.7136e+00],
        [-1.0560e+00, -6.0338e-01, -2.2632e+00, -2.0789e+00, -1.3894e+00,
        -7.4707e-01, -5.6277e-01, -2.0304e+00, -7.9336e-01, -2.1309e+00,
        -1.4617e+00],
        [-2.8569e+00,  1.5107e+00, -3.9784e-01, -1.4395e+00, -1.0735e+00,
        -8.4347e-01, -5.4561e-01,  2.1713e-02,  5.2930e-02, -6.8428e-01,
        -7.4316e-01],
        [-2.1679e+00, -2.0094e+00,  1.0398e+00, -1.5237e-01, -1.3012e+00,
        -1.3358e+00,  7.8404e-01,  1.2858e+00,  7.9492e-02, -2.6088e-01,
        7.9342e-01],
        [ 2.6121e-01, -3.0881e+00,  2.5165e-02,  2.0338e+00,  1.0868e+00,
        1.9849e-01, -1.6854e+00, -5.0611e-02,  9.1003e-01,  3.3840e-01,
        -3.5249e-01],
        [ 9.5256e-01,  4.8590e-01, -9.3685e-01,  4.0024e-01, -5.0403e-01,
        8.7469e-02,  6.2727e-01,  5.5579e-01,  9.2688e-01,  3.9535e-01,
        5.9070e-01],
        [ 6.9449e-01,  8.0825e-01, -1.1992e+00, -9.7262e-01,  2.0402e-01,
        9.1987e-01,  1.6221e-01, -1.3533e+00,  5.8699e-01,  2.9566e-01,
        7.8926e-01],
        [-6.6234e-01,  5.4043e-01,  2.1175e-01,  1.8532e-01, -2.5611e-01,
        -1.4226e-02, -8.6193e-02, -1.7941e-01,  9.7519e-01,  5.7587e-01,
        2.9208e-01],
        [ 5.8813e-01, -6.2854e-01,  7.1162e-01,  4.5879e-01,  1.7431e-01,
        2.6236e-01,  4.3695e-01,  4.2049e-01,  5.0743e-01,  6.5013e-01,
        -6.2905e-04],
        [ 1.0536e-01, -1.1915e-01, -1.8992e-01,  6.9262e-01,  9.7283e-01,
        -9.7259e-02,  4.4404e-01, -2.2113e-01, -8.5840e-02,  3.9737e-01,
        4.3466e-01],
        [ 5.0410e-01,  3.8175e-01, -1.0441e+00,  3.3980e-01,  9.5678e-01,
        5.1907e-01, -2.9969e-02,  2.6303e-01,  1.4810e-01,  3.4940e-01,
        4.3466e-01]], grad_fn=<SelectBackward0>)
```

4. Model(GRU + CNN)

```
1 batch1 = nn.BatchNorm2d(64)
2 out2 = batch1(out1)
3 print(out2.shape)
4 out2[0][0]
```

```
torch.Size([1, 64, 11, 11])
tensor([[ 6.5612e-01,  1.3315e-01,  1.8540e-01,  1.5603e+00,  2.5513e+00,
          6.5685e-01, -2.0704e-01,  7.7814e-01,  2.1785e+00, -3.0944e-01,
          2.7135e+00],
        [-1.0560e+00, -6.0835e-01, -2.2632e+00, -2.0789e+00, -1.3894e+00,
         -7.4707e-01, -5.6277e-01, -2.0304e+00, -7.9336e-01, -2.1309e+00,
         -1.4617e+00],
        [-2.5565e+00,  1.5107e+00, -3.9784e-01, -1.4395e+00, -1.0735e+00,
         -8.4347e-01, -5.4561e-01,  2.1713e-02,  5.2930e-02, -6.8428e-01,
         -7.4315e-01],
        [-2.1672e+00, -2.0094e+00,  1.0398e+00, -1.5237e-01, -1.3012e+00,
         -1.3355e+00,  7.8404e-01,  1.2855e+00,  7.9452e-02, -2.6089e-01,
          7.5842e-01],
        [ 2.5121e-01, -3.0881e+00,  2.5165e-02,  2.0938e+00,  1.0868e+00,
          1.5845e-01, -1.5854e+00, -5.0611e-02,  9.1003e-01,  3.3840e-01,
         -3.5240e-01],
        [ 9.5255e-01,  4.5590e-01, -9.3685e-01,  4.0024e-01, -5.0403e-01,
          8.7465e-02,  6.2727e-01,  5.5573e-01,  9.2688e-01,  3.5535e-01,
          5.5070e-01],
        [ 6.9445e-01,  8.0825e-01, -1.1992e+00, -9.7262e-01,  2.0402e-01,
          9.1987e-01,  1.5221e-01, -1.5533e+00,  5.8609e-01,  2.0566e-01,
          7.5925e-01],
        [-6.5234e-01,  5.4045e-01,  2.1175e-01,  1.8532e-01, -2.5611e-01,
         -1.4225e-02, -8.5193e-02, -1.7941e-01,  9.7519e-01,  5.7527e-01,
          2.5205e-01],
        [ 5.5813e-01, -6.2854e-01,  7.1162e-01,  4.5879e-01,  1.7431e-01,
          2.5235e-01,  4.3695e-01,  4.2045e-01,  5.0743e-01,  6.5013e-01,
         -6.2905e-04],
        [ 1.0535e-01, -1.1915e-01, -1.8902e-01,  6.0262e-01,  9.7233e-01,
         -9.7255e-02,  4.4404e-01, -2.2113e-01, -8.5840e-02,  3.9737e-01,
          4.5465e-01],
        [ 5.0410e-01,  3.8175e-01, -1.0441e+00,  3.3980e-01,  9.5678e-01,
          5.1907e-01, -2.9965e-02,  2.5303e-01,  1.4810e-01,  3.4940e-01,
          4.5465e-01]], grad_fn=<SelectBackward0>)
```

Activation function(GELU)



```
1 opti1 = nn.GELU()
2 out3 = opti1(out2)
3 out3.shape
4 (out3[0][0])
```

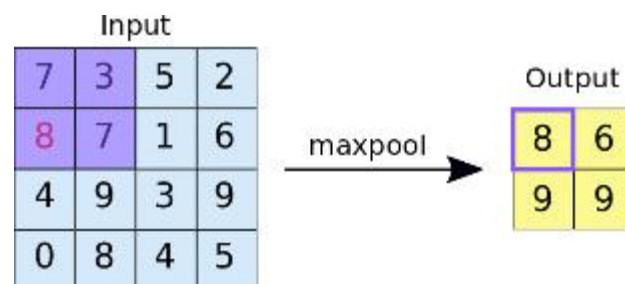
```
tensor([[ 4.9781e-01,  7.3624e-02,  1.0633e-01,  1.4677e+00,  2.5377e+00,
          5.1783e-01, -1.1383e-01,  6.0631e-01,  2.1456e+00, -1.1712e-01,
          2.7046e+00],
        [-1.5363e-01, -1.6480e-01, -2.6734e-02, -3.9113e-02, -1.1442e-01,
         -1.6397e-01, -1.6140e-01, -4.2958e-02, -1.6961e-01, -3.5265e-02,
         -1.0512e-01],
        [-6.1104e-03,  1.4119e+00, -1.3740e-01, -1.0796e-01, -1.5192e-01,
         -1.6826e-01, -1.5968e-01,  1.1045e-02,  2.7582e-02, -1.6895e-01,
         -1.6395e-01],
        [-3.2702e-02, -4.4703e-02,  8.8469e-01, -6.6958e-02, -1.2569e-01,
         -1.2131e-01,  6.1429e-01,  1.1581e+00,  4.2265e-02, -1.0359e-01,
          6.2381e-01],
        [ 1.5752e-01, -3.1101e-03,  1.2835e-02,  1.9911e+00,  9.3623e-01,
          1.1486e-01, -7.7459e-02, -2.4284e-02,  7.4495e-01,  2.1403e-01,
         -1.2768e-01],
        [ 7.9024e-01,  3.3355e-01, -1.6340e-01,  2.6236e-01, -1.5480e-01,
          4.6783e-02,  4.6089e-01,  3.9507e-01,  7.6283e-01,  2.5845e-01,
          4.2586e-01],
        [ 5.2525e-01,  6.3894e-01, -1.3818e-01, -1.6084e-01,  1.1850e-01,
          7.5537e-01,  9.1558e-02, -1.1907e-01,  4.2345e-01,  1.8220e-01,
          6.1959e-01],
        [-1.6815e-01,  3.8130e-01,  1.2363e-01,  1.0628e-01, -1.0217e-01,
         -7.0322e-03, -4.0136e-02, -7.6932e-02,  8.1455e-01,  4.1327e-01,
          1.7959e-01],
        [ 4.2450e-01, -1.6645e-01,  5.4200e-01,  3.1052e-01,  9.9213e-02,
          1.5833e-01,  2.9229e-01,  2.7875e-01,  3.5220e-01,  4.8252e-01,
         -3.1437e-04],
        [ 5.7102e-02, -5.3926e-02, -8.0656e-02,  5.2344e-01,  8.1200e-01,
         -4.4862e-02,  2.9817e-01, -9.1214e-02, -3.9984e-02,  2.6006e-01,
          2.9040e-01],
        [ 3.4929e-01,  2.4764e-01, -1.5476e-01,  2.1509e-01,  7.9476e-01,
          3.6238e-01, -1.4626e-02,  1.5880e-01,  8.2765e-02,  2.2243e-01,
          2.9040e-01]], grad_fn=<SelectBackward0>)
```


4. Model(GRU + CNN)

```
1 opt1 = nn.GELU()
2 out3 = opt1(out2)
3 out3.shape
4 (out3[0][0])
```

```
tensor([[ 4.9781e-01,  7.3624e-02,  1.0633e-01,  1.4677e+00,  2.5377e+00,
          5.1783e-01, -1.1383e-01,  6.0831e-01,  2.1466e+00, -1.1712e-01,
          2.7046e+00],
        [-1.5363e-01, -1.6480e-01, -2.6734e-02, -3.9113e-02, -1.1442e-01,
         -1.6997e-01, -1.6140e-01, -4.2958e-02, -1.6961e-01, -3.5265e-02,
         -1.0512e-01],
        [-6.1104e-03,  1.4119e+00, -1.3740e-01, -1.0796e-01, -1.5192e-01,
         -1.6826e-01, -1.5968e-01,  1.1045e-02,  2.7582e-02, -1.6895e-01,
         -1.6996e-01],
        [-3.2702e-02, -4.4703e-02,  6.8469e-01, -6.6958e-02, -1.2569e-01,
         -1.2131e-01,  6.1429e-01,  1.1581e+00,  4.2265e-02, -1.0359e-01,
          6.2381e-01],
        [ 1.5752e-01, -3.1101e-03,  1.2835e-02,  1.9911e+00,  9.3623e-01,
          1.1486e-01, -7.7459e-02, -2.4284e-02,  7.4495e-01,  2.1403e-01,
         -1.2768e-01],
        [ 7.9024e-01,  3.3356e-01, -1.6340e-01,  2.6236e-01, -1.5480e-01,
          4.6783e-02,  4.6089e-01,  3.9507e-01,  7.6283e-01,  2.5845e-01,
          4.2686e-01],
        [ 5.2525e-01,  6.3894e-01, -1.3818e-01, -1.6084e-01,  1.1850e-01,
          7.5537e-01,  9.1558e-02, -1.1907e-01,  4.2345e-01,  1.8220e-01,
          6.1959e-01]])
```

Max-Pooling & Reshape



```
1 Pool1 = nn.MaxPool2d((3,3))
2 out4 = Pool1(out3)
3 out4.shape
4 cnn_out = torch.reshape(out4,(1,288,-1))
5 print(cnn_out.shape)
6 cnn_out
```

```
torch.Size([1, 288, 2])
tensor([[[[ 1.4119e+00,  2.5377e+00],
          [ 2.1466e+00,  8.8469e-01],
          [ 1.9911e+00,  1.1581e+00],
          [ 6.3894e-01,  7.5537e-01],
          [ 8.1455e-01,  3.2357e+00],
          [ 2.0508e+00,  2.1387e+00],
          [ 1.2468e+00,  9.6917e-01],
          [ 5.1291e-01,  4.3646e-01],
          [ 1.8598e-02,  3.1642e-02],
          [ 2.6429e+00,  2.8486e-01],
          [ 6.5287e-01,  1.9474e+00],
          [ 8.2418e-01,  2.4485e-02],
          [ 1.1294e+00,  5.8659e-01],
          [ 9.8939e-01,  7.4055e-01],
          [ 6.3070e-01,  1.1087e+00],
          [ 1.6139e+00,  2.0318e+00],
          [ 2.4533e+00,  2.5359e+00],
          [ 1.0758e+00,  1.8824e+00],
          [ 2.2384e+00,  3.0895e-01],
          [ 2.6339e-01,  2.5383e+00],
          [ 5.5352e-01,  9.2229e-01],
          [ 1.0497e+00,  6.4886e-01],
          [ 1.1535e+00,  3.7798e+00],
          [ 7.8024e-01,  2.4156e+00],
          [ 2.7883e+00,  1.5911e+00],
          [ 3.0061e-01,  1.4013e+00],
          [ 4.1781e-01,  9.9199e-01],
          [ 3.4100e+00,  3.1764e+00],
          [ 2.9760e+00,  1.1447e+00],
          [ 5.9553e-01,  8.6133e-01],
          [ 1.5682e-01,  1.1398e-01],
          [ 1.4693e-01,  2.4255e+00]]]])
```

4. Model(GRU + CNN)

```
In [19]: from sklearn.preprocessing import MinMaxScaler, StandardScaler, RobustScaler
```

```
def my_scale(lst):  
    n = len(lst)  
    x = np.array(lst).reshape(-1,1)  
    scaler_robust = RobustScaler()  
    scaler_robust.fit(x)  
    k = scaler_robust.transform(x)  
    kk = k.reshape(n)  
    return list(np.round(kk, 4))
```

Standard Scaler

$$\frac{x_i - \text{mean}(\mathbf{x})}{\text{stdev}(\mathbf{x})}$$

MinMax Scaler

$$\frac{x_i - \min(\mathbf{x})}{\max(\mathbf{x}) - \min(\mathbf{x})}$$

Robust Scaler

$$\frac{x_i - Q_1(\mathbf{x})}{Q_3(\mathbf{x}) - Q_1(\mathbf{x})}$$

```
In [13]: df_train['Wspd_seq'] = df_train.apply(  
        lambda x: [round(r**3,4) for r in x['Wspd_seq']],  
        axis=1,  
        )
```

```
In [14]: df_train['Wspd_seq']
```

```
Out[14]: 0      [0.0244, 0.2054, 0.9127, 2.6281, 7.3014, 11.08...  
1      [4.2515, 1.5209, 6.2295, 14.1725, 5.0884, 5.35...  
2      [19.0342, 20.7969, 18.6096, 18.8211, 14.1725, ...  
3      [1423.8281, 1211.3555, 1201.157, 876.4675, 104...  
4      [92.3454, 51.8951, 46.656, 42.5085, 27.8181, 2...  
...  
37044   [353.3932, 382.6572, 430.3689, 433.7981, 460.0...  
37045   [34.3281, 10.3602, 9.1293, 7.6454, 10.2183, 13...  
37046   [6.2295, 58.4111, 84.6045, 51.4788, 59.7765, 5...  
37047   [252.436, 211.7087, 228.0991, 174.6769, 125.0,...  
37048   [296.741, 189.1192, 329.9394, 135.0057, 91.733...  
Name: Wspd_seq, Length: 37049, dtype: object
```

4. Model(GRU + CNN)

```
class EarlyStopping:
    def __init__(self, patience=7, verbose=False, delta=0, path='checkpoint.pt', trace_func=print):

        self.patience = patience
        self.verbose = verbose
        self.counter = 0
        self.best_score = None
        self.early_stop = False
        self.val_loss_min = np.Inf
        self.delta = delta
        self.path = path
        self.trace_func = trace_func
    def __call__(self, val_loss, model):

        score = -val_loss

        if self.best_score is None:
            self.best_score = score
            self.save_checkpoint(val_loss, model)
        elif score < self.best_score + self.delta:
            self.counter += 1
            self.trace_func(f'EarlyStopping counter: {self.counter} out of {self.patience}')
            if self.counter >= self.patience:
                self.early_stop = True
        else:
            self.best_score = score
            self.save_checkpoint(val_loss, model)
            self.counter = 0

    def save_checkpoint(self, val_loss, model):
        if self.verbose:
            self.trace_func(f'Validation loss decreased ({self.val_loss_min:.6f} → {val_loss:.6f}). Saving model ...')
        torch.save(model.state_dict(), self.path)
        self.val_loss_min = val_loss
```

4. Model(GRU + CNN)

```
In [30]: def train(model, optimizer, (train_loader, device):
    model.to(device)
    criterion = nn.MSELoss().to(device)
    metric = nn.L1Loss().to(device)

    ts = []
    pred_list = []
    label_list = []
    val_loss_list = []
    val_acc_list = []
    loss_list = []
    early_stopping = EarlyStopping(patience = 5, verbose = True)
    for epoch in range(100):
        model.train()

        for seq, space_data, label in tqdm(train_loader):
            seq = seq.type(torch.FloatTensor).to(device)

            space_data = torch.reshape(space_data, (-1, 1, 11, 11)).to(device)
            space_data = space_data.type(torch.FloatTensor)

            label = label.type(torch.FloatTensor).to(device)

            pred = model(seq, space_data)

            loss = criterion(pred.squeeze() / 1000, label / 1000)
            loss_list.append(loss.item())
            loss.backward()
            optimizer.step()
            optimizer.zero_grad()

            pred_list.extend(pred.squeeze().cpu().detach().numpy())
            label_list.extend(label.squeeze().cpu().detach().numpy())

        del pred
        del seq
        del space_data
        del label

        for val_seq, val_space_data, val_label in tqdm(val_loader):
            val_seq = val_seq.type(torch.FloatTensor).to(device)
            val_space_data = torch.reshape(val_space_data, (-1, 1, 11, 11)).to(device)
            val_space_data = val_space_data.type(torch.FloatTensor)

            val_label = val_label.type(torch.FloatTensor)
            val_pred = model(val_seq, val_space_data).cpu()
```

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5. Test

```
class myDataset(mn.Dataset):
    def __init__(self, df):

        self.seq_list1 = list(df['seq_seq1'])
        self.seq_list2 = list(df['seq_seq2'])

        self.seq_list3 = list(df['img_seq1'])
        self.seq_list4 = list(df['img_seq2'])

        self.seq_list5 = list(df['img_space1'])

        self.label_list = df['label'].values

    def __getitem__(self, index):

        seq = np.concatenate((self.seq_list1[index], self.seq_list2[index], self.seq_list3[index], self.seq_list4[index]))
        seq = np.array(seq).astype('float')

        image = np.array(self.seq_list5[index]).astype('float')
        image = image[11, 11, 1]

        label = np.array(self.label_list[index]).astype('float')

        seq = torch.tensor(seq, device = 'cuda')
        space_data = torch.tensor(image, device = 'cuda')

        return seq, space_data, label

    def __len__(self):
        return len(self.seq_list1)

def predict(model, test_loader, device):
    model.to(device)
    model.eval()

    pred_list = []

    for seq, space_data, label in test_loader:
        seq = seq.type(torch.FloatTensor).to(device)
        space_data = torch.reshape(space_data, (-1, 1, 1, 1, 1)).to(device)
        space_data = space_data.type(torch.FloatTensor)
        label = label.type(torch.FloatTensor).to(device)

        pred = model(seq, space_data)

        pred_list.extend(pred.squeeze().cpu().detach().numpy())

    return pred_list
```

5. Test

```
In [10]: def forecast():
    torch_device = 'cuda' if torch.cuda.is_available() else 'cpu'

    os.environ['CUDA_VISIBLE_DEVICES'] = '-1'

    test_x = pd.read_csv('training_data.csv')
    test_x = test_x.fillna(0)
    test_x = test_x.sort_values(['Turbid', 'Day', 'Timestamp'], ascending=True).reset_index(drop=True)

    model = RNN()

    model.load_state_dict(torch.load('ourbest2band82snuff1e70s_indef_a_normal_in05excellent2yearsupdate9-populars'))

    path_to_dist_dict = 'dist_dict.pickle'
    with open(path_to_dist_dict, 'rb') as f:
        dist_dict = pickle.load(f)

    df_group = test_x[['Day', 'Timestamp', 'Paly']].groupby(['Day', 'Timestamp'], as_index=False).agg(list)
    print(df_group)
    df_group.columns = ['Day', 'Timestamp', 'Paly_list']

    for turbid in range(24):

        turb_data = test_x[test_x['Turbid'] == turbid+1].reset_index(drop=True)
        turb_data = pd.merge(turb_data, df_group, how='left', on=['Day', 'Timestamp'])
        turb_data['Paly_space'] = turb_data['Paly_list'].apply(lambda x: [x[-1]] if i in dist_dict[turbid+1][1:21])

        df_test = pd.concat([df_test, pd.DataFrame({'Food_seq': list(turb_data['Food']),
                                                    'Paly_seq': list(turb_data['Paly']),
                                                    'Temp_seq': list(turb_data['Temp']),
                                                    'Humid_seq': list(turb_data['Humid']),
                                                    'Rain_seq': list(turb_data['Rain']),
                                                    'Paly_space': list(turb_data['Paly_space']),
                                                    'targer': [0]*20})

        df_test['comp_seq'] = df_test.apply(get_comp, axis=1)
        if turbid==0:
            test_new = df_test.copy()
        else:
            test_new = pd.concat([test_new, df_test])

    test_dataset = nn.DataLoader(test_new)
    test_loader = DataLoader(test_dataset,
                              batch_size=8,
                              shuffle=False,
                              num_workers=0)

    pred_list = pred_gnn(model, test_loader, device)
```

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감사합니다.