2022 Inha AI Challenge

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목차

1. Abstract

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

목표 : 134개 터빈의 2일 동안의 Patv 값 예측

TurbID - 발전기 ID

Day - 날짜

Tmstamp - 시간

Wspd - 풍속

Wdir - [illegible]빈이 바라보[illegible] 각도[illegible] 실[illegible] 바람 방[illegible] 각도 차이

Etmp [illegible] 외부[illegible]

Itmp - [illegible] 온도

Ndir - 터빈이 바라보는 방향 각도

Pab - 터빈 당 3개의 날이 있으며 각각의 각도가 다름

Prtv - 무효전력 : 에너지원을 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	[illegible]	[illegible]	[illegible]	
10	9	[illegible]	[illegible]	
11	10	[illegible]	[illegible]	
12	11	[illegible]	[illegible]	
13	12	[illegible]	[illegible]	
14	[illegible]	[illegible]	[illegible]	
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	

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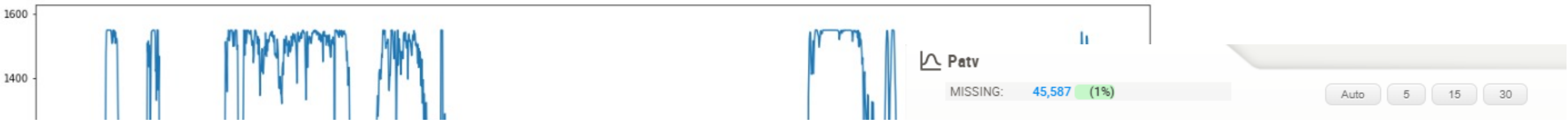
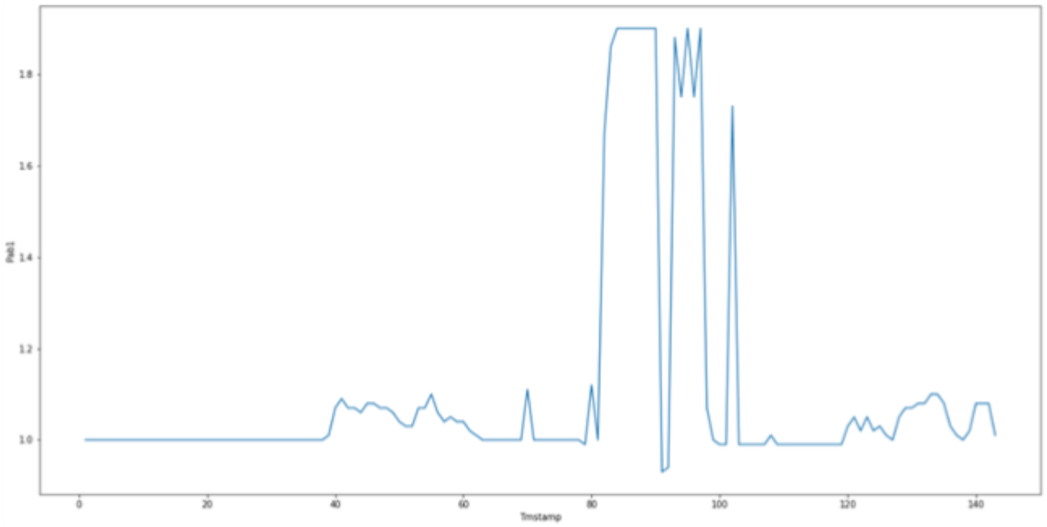
목차

2. Feature

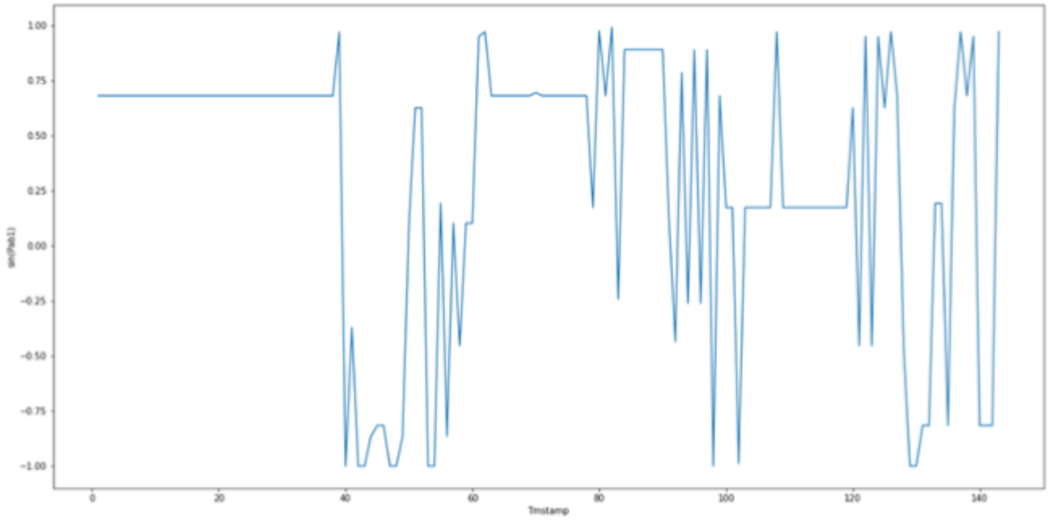


(TurbID == 1 & Day == 1)

pab1

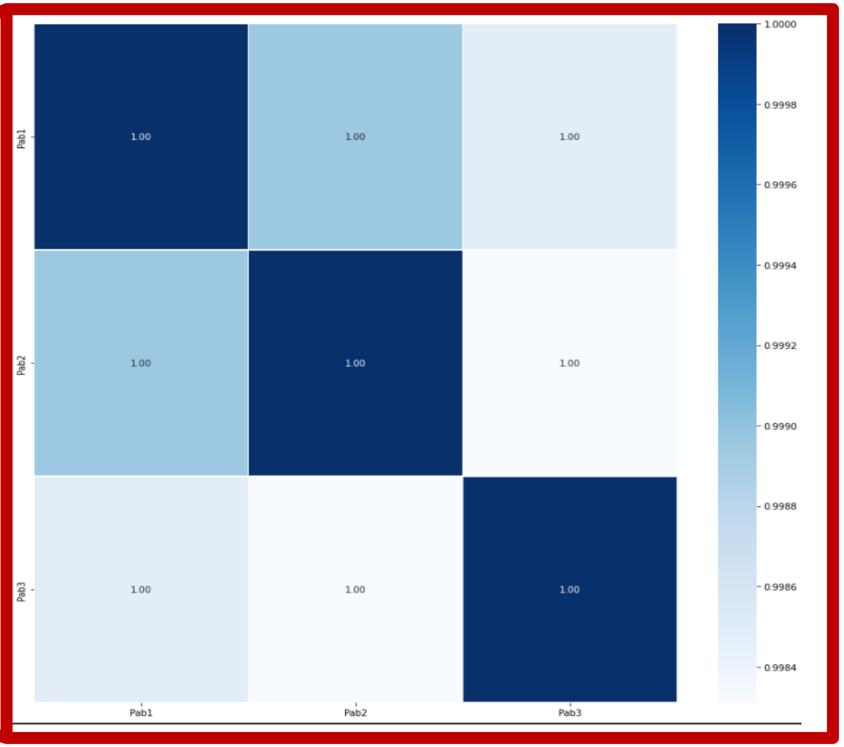


$\sin(pab1)$



2. Feature


TurbID 1.0000 0.0000 -0.0411 -0.0004 -0.0486 -0.0597 -0.0034 0.0252 0.0257 0.0248 0.0393 -0.0620
Day 0.0000 1.0000 -0.0921 0.0024 -0.0659 -0.2328 0.0545 0.0138 0.0141 0.0137 -0.0776 -0.0286
Wspd -0.0921 1.0000 -0.0154 0.0259 0.1163 -0.0499 -0.3824 -0.3826 -0.3823 0.7948
Wdir -0.0004 0.0024 -0.0154 1.0000 -0.0030 -0.0024 0.0084 0.0230 0.0228 0.0225 0.0027 -0.0190
Etmp -0.0486 -0.0659 0.0259 -0.0030 1.0000 0.1498 -0.0198 0.0038 0.0036 0.0041 0.0132 0.0137
Itmp -0.0597 -0.2328 0.1163 -0.0024 0.1498 1.0000 -0.0017 -0.0028 -0.0028 -0.0025 0.0620 0.0996
Ndir -0.0034 0.0545 -0.0499 0.0084 -0.0198 -0.0017 1.0000 0.0051 0.0054 0.0045 -0.0423
Pab1 0.0252 0.0138 -0.3824 0.0230 0.0038 -0.0028 0.0051 1.0000 0.9990 0.9985 0.1534 -0.5052
Pab2 0.0257 0.0141 -0.3826 0.0228 0.0036 -0.0028 0.0054 0.9990 1.0000 0.9983 0.1533 -0.5048
Pab3 0.0248 0.0137 -0.3823 0.0225 0.0041 -0.0025 0.0045 0.9985 0.9983 1.0000 0.1532 -0.5046
Prtv 0.0393 -0.0776 0.1983 0.0027 0.0132 0.0620 -0.0423 0.1534 0.1533 0.1532 1.0000
Patv -0.0620 -0.0286 0.7948 -0.0190 0.0137 0.0996 -0.0354 -0.5052 -0.5048 -0.5046 0.2263 1.0000
TurbID Day Wspd Wdir Etmp Itmp Ndir Pab1 Pab2 Pab3 Prtv Patv
1.0 0.8 0.6 0.4 0.2 0.0 -0.2

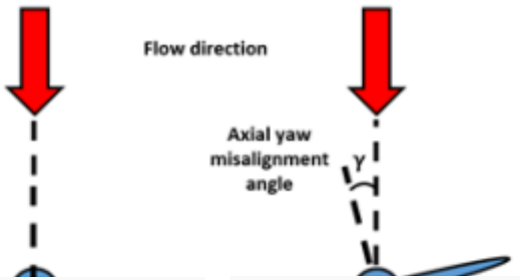

Pab1 1.00 1.00 1.00
Pab2 1.00 1.00 1.00
Pab3 1.00 1.00 1.00
Pab1 Pab2 Pab3
1.0000 0.9998 0.9996 0.9994 0.9992 0.9990 0.9988 0.9986 0.9984

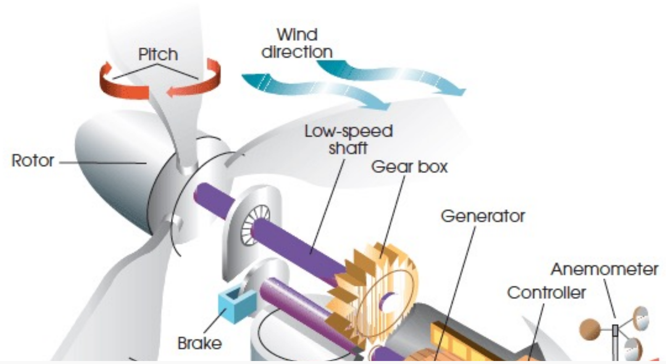
2. Feature

Patv

Wspd

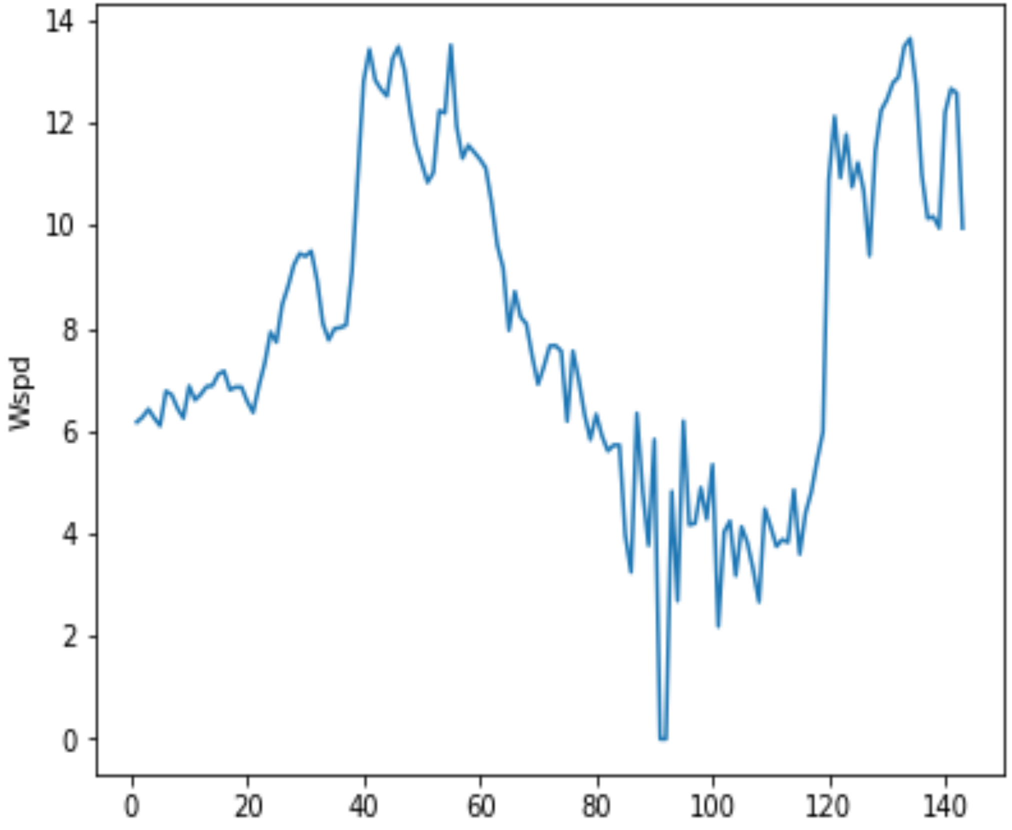
$$\dot{P} = \frac{1}{2} \times \rho \times A \times (V \times \cos\gamma)^3$$

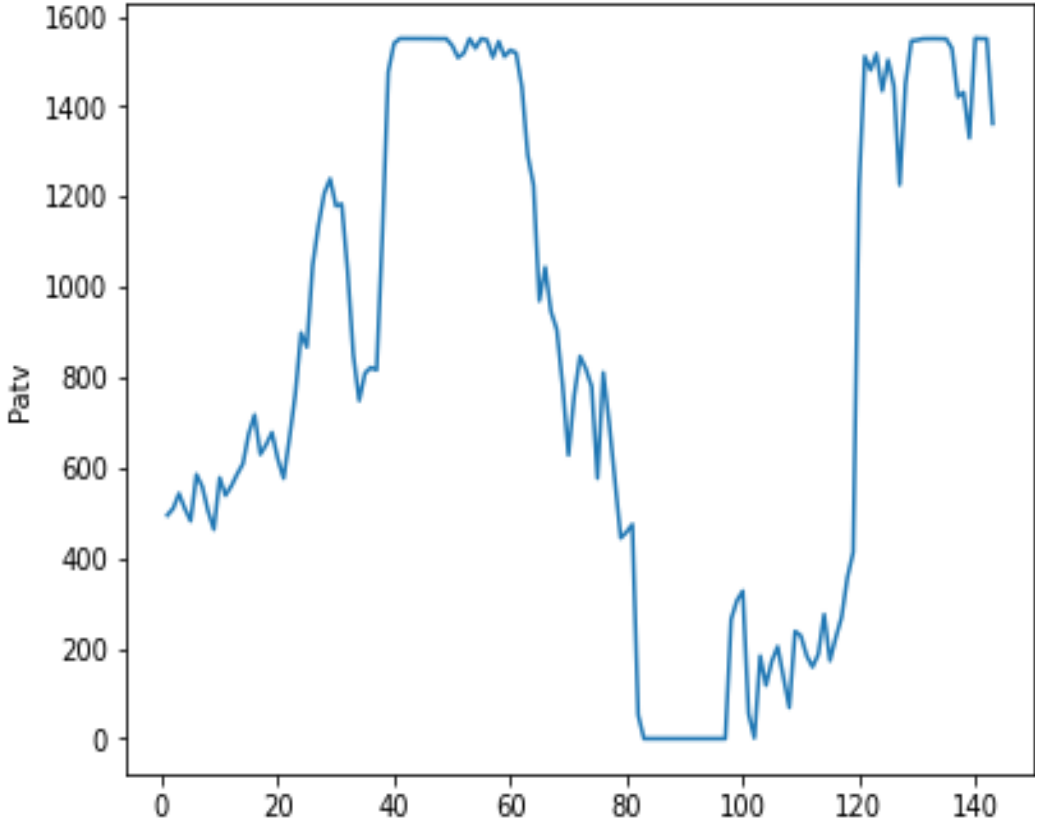




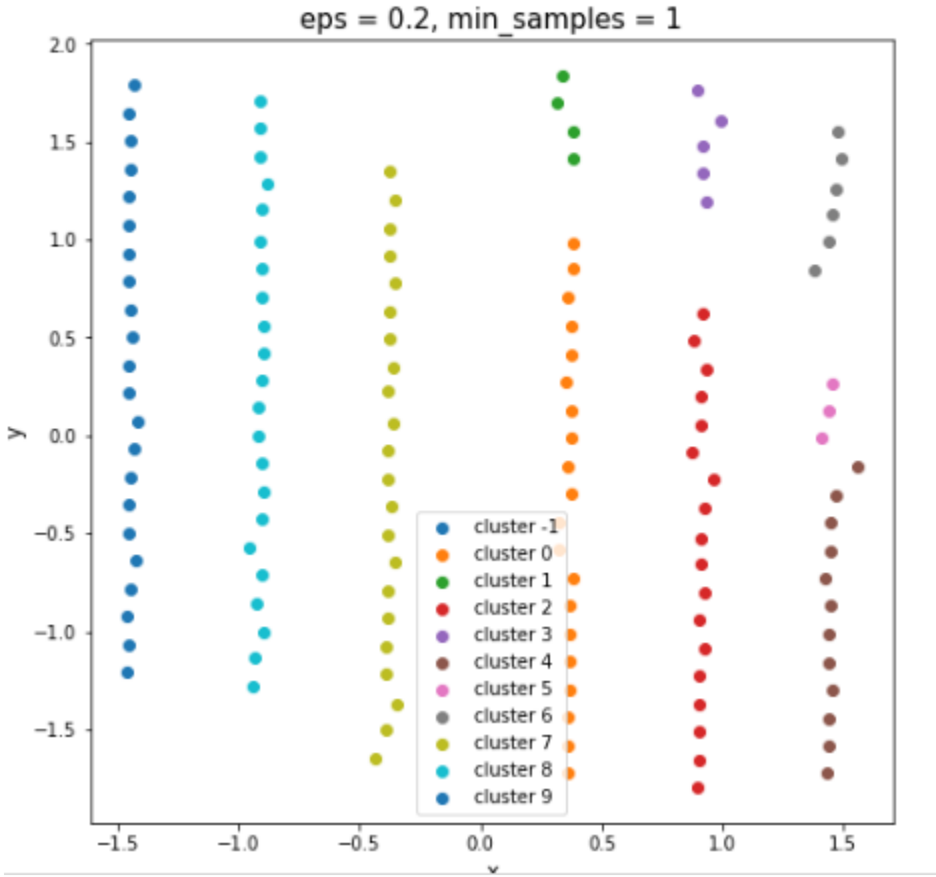
2. Feature

(TurbID == 1 & Day == 1)
Wspd 와 Patv 비교





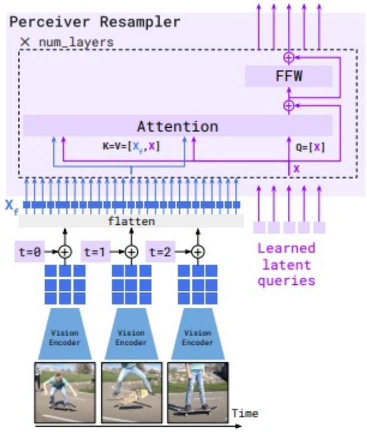
공간정보 .. ?




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

	cl0	cl1	cl2	cl3	cl4	cl5	cl6	cl7	cl8	cl9	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




```python
def perceiver_resampler(
    x_f,  # The [T, S, d] visual features (T=time, S=space)
    time_embeddings,  # The [T, 1, d] time pos embeddings.
    x,  # R learned latents of shape [R, d]
    num_layers,  # Number of layers
):
  """The Perceiver Resampler model."""

  # Add the time position embeddings and flatten.
  x_f = x_f + time_embeddings
  x_f = flatten(x_f)  # [T, S, d] -> [T * S, d]
  # Apply the Perceiver Resampler layers.
  for i in range(num_layers):
    # Attention.
    x = x + attention_i(q=x, kv=concat([x_f, x]))
    # Feed forward.
    x = x + ffw_i(x)
  return x
```

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_f. 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 no 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_f, 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

256x256 이미지 예시

11

Patv값	Patv값	Patv값	…	…	…					
					…	…	…	Patv값	Patv값	Patv값

11

11x11 이미지 예시

목차

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3. Prepare

```python
input_len = 144 # id 한 개당 하루에 생성되는 row의 갯수 (24hour / 10minute = 144)

for turbid in range(134): # 터빈 아이디의 갯수
    # print(turbid)
    full_dict = collections.defaultdict(list)
    turb_data = df[df['TurbID']==turbid+1].reset_index(drop=True)
    ls = list(turb_data['Patv'])
    for i in range(0, len(ls)-288-input_len): # range(0, ) # 288 (id 당 예측해야 하는 patv 갯수 2일 -> 144 * 2)
        if i % 10000 == 1: print(i)
        # i 가 0 이면 Wspd의 처음 시작 1일 0시 00분 부터 1일 23시 50분까지의 Wspd 리스트 추가
        full_dict['Wspd_seq'].append(list(turb_data['Wspd'])[i:i+input_len])
        full_dict['Patv_seq'].append(list(turb_data['Patv'])[i:i+input_len])
        full_dict['Etmp_seq'].append(list(turb_data['Etmp'])[i:i+input_len])
        full_dict['Itmp_seq'].append(list(turb_data['Itmp'])[i:i+input_len])
        full_dict['Pab1_seq'].append(list(turb_data['Pab1'])[i:i+input_len])

        full_dict['target'].append(list(turb_data['Patv'])[i+input_len:i+input_len+288])
        # i 가 0이면 [144: 144 + 288]  (288개의 patv 값 저장)
    df_his = pd.DataFrame(full_dict)
    df_his.to_csv('turbine_data'+str(turbid+1)+'.csv', index=False)
```

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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	Pab1	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	Pab1_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, 1.0, 1.0, ...	[1468.21, 718.12, 442.15, 196.04, 234.35, 124....
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, 584.7...	[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, 1.0, 1.0, ...	[718.12, 442.15, 196.04, 234.35, 124.94, 179.0...
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, 557.9...	[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, 1.0, 1.0, ...	[442.15, 196.04, 234.35, 124.94, 179.06, 253.2...
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, 503.9...	[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, 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, 463.3...	[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, 1.0, 1.0, ...	[234.35, 124.94, 179.06, 253.25, 347.0, 249.3,...

3. Prepare

```
1 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	target
0	[0.0, 6.17, 6.27, 6.42, 6.25, 6.1, 6.77, 6.7, ...	[1468.21, 718.12, 442.15, 196.04, 234.35, 124....
1	[6.17, 6.27, 6.42, 6.25, 6.1, 6.77, 6.7, 6.44,...	[718.12, 442.15, 196.04, 234.35, 124.94, 179.0...
2	[6.27, 6.42, 6.25, 6.1, 6.77, 6.7, 6.44, 6.25,...	[442.15, 196.04, 234.35, 124.94, 179.06, 253.2...
3	[6.42, 6.25, 6.1, 6.77, 6.7, 6.44, 6.25, 6.87,...	[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, ...	[234.35, 124.94, 179.06, 253.25, 347.0, 249.3,...

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```

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

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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','Tmstamp'])
             selected_df['Patv_space'] = selected_df['Patv_list'].apply(lambda x: [x[k-1] for k in near_turbs])
             df_tmp['Patv_space'] = list(selected_df['Patv_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,  1.68s/it]

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

         train = drop_abnormal(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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│   ├── dist_dict.pickle
```

3. Prepare

TurbID	index	Wspd_seq	Patv_seq	Etmp_seq	Itmp_seq	Pab1_seq	Patv_space	target
1	62	[10.45, 9.61, 9.17, 7.96, 8.71, 8.22, 8.08, 7....	[1442.49, 1292.15, 1225.7, 969.62, 1043.58, 94...	[32.55, 32.81, 33.04, 33.27, 33.57, 33.67, 33....	[45.33, 45.42, 45.61, 45.84, 46.09, 46.09, 46....	[1.01, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.11...	[379.1, 498.28, 505.66, 505.88, 508.71, 390.74...	[593.99, 525.69, 591.37, 444.78, 403.78, 610.5...
1	151	[4.63, 5.4, 4.73, 4.43, 4.85, 5.14, 3.7, 4.87,...	[253.25, 347.0, 249.3, 205.12, 254.04, 323.51,...	[26.25, 26.01, 25.84, 25.49, 25.27, 24.95, 24....	[39.97, 39.09, 38.32, 37.69, 37.15, 36.77, 36....	[0.99, 0.99, 0.99, 0.99, 0.99, 1.0, 0.99, 0.99...	[980.43, 1457.23, 1178.17, 1100.27, 1474.57, 1...	[1549.82, 1549.65, 1549.37, 1489.51, 1502.11, ...
1	258	[3.04, 3.78, 4.05, 4.4, 3.65, 3.59, 3.11, 2.77...	[121.01, 164.86, 205.14, 240.6, 163.27, 145.8,...	[31.84, 31.85, 31.9, 31.75, 31.53, 31.34, 31.1...	[39.96, 39.91, 39.86, 39.75, 39.51, 39.4, 39.3...	[0.99, 0.99, 0.99, 0.99, 0.99, 0.99, 0.99, 0.9...	[1507.5, 1466.76, 1489.21, 1492.34, 1447.56, 1...	[1490.34, 1481.3, 1489.68, 1530.56, 1521.49, 1...
1	393	[11.18, 11.57, 11.75, 11.43, 11.13, 11.23, 10....	[1511.29, 1522.37, 1531.61, 1509.51, 1500.73, ...	[29.31, 29.29, 29.27, 29.33, 29.44, 29.4, 29.3...	[42.92, 43.02, 42.99, 43.01, 43.03, 43.24, 43....	[1.02, 1.04, 1.05, 1.04, 1.03, 1.04, 1.03, 1.0...	[343.36, 440.9, 378.82, 445.85, 537.92, 485.14...	[436.32, 414.8, 427.89, 434.48, 382.58, 489.54...
1	467	[11.55, 11.55, 11.77, 11.73, 12.02, 12.54, 12....	[1451.01, 1544.67, 1531.91, 1546.11, 1531.58, ...	[22.28, 22.2, 22.14, 22.09, 22.03, 22.07, 22.1...	[37.19, 37.09, 37.09, 37.05, 37.05, 36.99, 36....	[1.07, 1.06, 1.07, 1.07, 1.07, 1.09, 1.08, 1.0...	[819.56, 883.94, 900.01, 882.72, 1234.27, 833....	[1422.55, 1209.65, 1397.94, 1464.29, 1550.32, ...
1	486	[11.89, 12.66, 12.66, 11.27, 11.01, 12.51, 12....	[1510.99, 1528.67, 1504.16, 1510.82, 737.9, 15...	[22.85, 22.94, 23.12, 23.3, 23.64, 23.97, 23.9...	[37.49, 37.41, 37.43, 37.52, 37.86, 38.01, 37....	[1.07, 1.09, 1.09, 1.05, 1.42, 1.08, 1.07, 1.0...	[-0.3, -0.3, 773.5, 683.16, -0.3, 693.54, 0.0,...	[1543.78, 1508.18, 1493.89, 1517.56, 1515.91, ...
1	495	[12.25, 12.03, 12.12, 12.59, 11.79, 12.39, 12....	[1542.44, 1547.11, 1534.13, 1540.59, 1527.62, ...	[24.72, 25.05, 25.42, 25.7, 26.0, 26.36, 26.56...	[38.35, 38.56, 38.92, 39.17, 39.42, 39.83, 40....	[1.07, 1.06, 1.07, 1.08, 1.06, 1.07, 1.06, 1.0...	[-0.3, -0.3, 241.69, 254.45, -0.3, 276.08, 0.0...	[1518.48, 1512.33, 1489.15, 1470.04, 1490.43, ...
1	505	[12.69, 13.02, 12.68, 12.65, 12.53, 12.55, 12....	[1528.23, 1545.66, 1542.25, 1535.52, 1548.12, ...	[27.75, 27.9, 28.15, 28.38, 28.55, 28.78, 29.1...	[41.04, 41.23, 41.35, 41.59, 41.78, 42.05, 42....	[1.08, 1.08, 1.08, 1.08, 1.08, 1.08, 1.07, 1.0...	[-0.3, -0.3, 225.95, 227.03, -0.3, 224.67, 0.0...	[1537.67, 1501.7, 1510.87, 1498.39, 1493.51, 1...
1	562	[6.28, 7.78, 8.83, 9.07, 8.71, 8.99, 9.07, 9.3...	[488.45, 802.05, 1074.46, 1079.95, 1033.42, 10...	[29.97, 29.92, 29.87, 29.7, 29.61, 29.44, 29.3...	[39.3, 39.71, 39.79, 39.77, 39.74, 39.94, 40.0...	[0.99, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0,...	[550.19, 871.86, 543.72, 775.48, 488.91, 868.0...	[400.06, 878.75, 1288.2, 1085.93, 1080.36, 873...
1	566	[8.71, 8.99, 9.07, 9.33, 9.25, 8.85, 9.21, 9.3...	[1033.42, 1095.11, 1154.13, 1191.08, 1184.36, ...	[29.61, 29.44, 29.32, 29.13, 28.96, 28.83, 28....	[39.74, 39.94, 40.08, 40.15, 40.22, 40.32, 40....	[1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, 1.0, ...	[1065.51, 1060.06, 1183.46, 1169.64, 793.06, 1...	[1080.36, 873.69, 754.98, 506.25, 361.97, 474....

거리가 가까운 121개의 터빈의 Patv 값을 feature로 사용

11 by 11 matrix로 만들어 **CNN의 이미지**로 활용

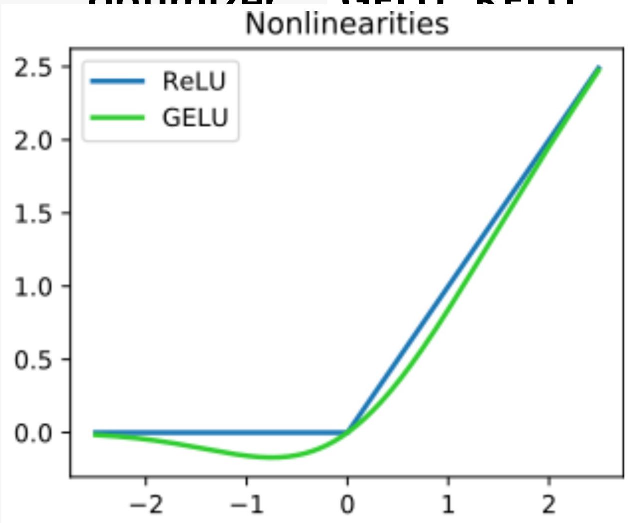
목차

인하대학교
INHA UNIVERSITY

4. Model(GRU + CNN)

```python
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.cnnLayer = 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):
#         z = torch.zeros([X.shape[0], 144, X.shape[1]], dtype="float32")
        z = torch.zeros([X.shape[0], 144, X.shape[1]])
        z = z.to(device)
#         x = torch.concat((X.transpose([0,2,1]),z), axis=1)
#         print(X.shape)
#         print(z)
#         print(type(x))
#         print(type(X))
#         print(type(z))
        x = torch.concat((torch.transpose(X,2,1),z), axis=1)
#         print(1)
        out1, _ = self.gru(x)
        out1 = self.dropout(out1)

        cnn_out = self.cnnLayer(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, 0.00001
optimizer = GELU, RELU



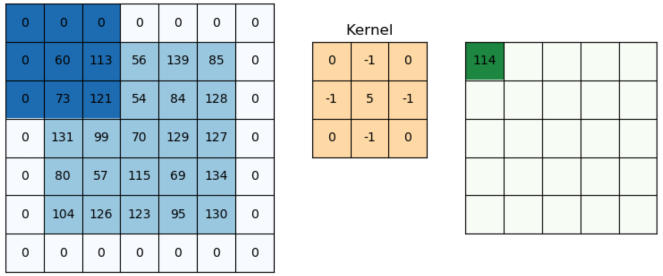
4. Model(GRU + CNN)

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

Ex) Convolution




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

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

```python
out1.shape
```

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

```python
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.]], grad_fn=<SliceBackward0>)
```

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

```
batch1 = nn.BatchNorm2d(64)
out2 = batch1(out1)
print(out2.shape)
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,  3.8176e-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)

```
batch1 = nn.BatchNorm2d(64)
out2 = batch1(out1)
print(out2.shape)
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,  3.8176e-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>)
```

Activation function(GELU)

```
opti1 = nn.GELU()
out3 = opti1(out2)
out3.shape
(out3[0][0])
```

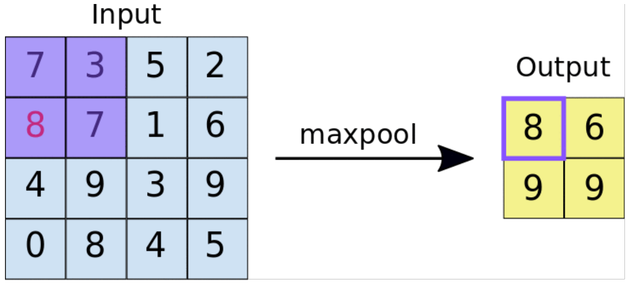
```
tensor([[ 4.9781e-01,  7.3624e-02,  1.0633e-01,  1.4677e+00,  2.5377e+00,
          5.1783e-01, -1.1383e-01,  6.0831e-01,  2.1466e+00, -1.1712e-01,
          2.7046e+00],
        [-1.5363e-01, -1.6480e-01, -2.6734e-02, -3.9113e-02, -1.1442e-01,
         -1.6997e-01, -1.6140e-01, -4.2958e-02, -1.6961e-01, -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,  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,  3.3356e-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],
        [-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,  2.7876e-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)

```
opti1 = nn.GELU()
out3 = opti1(out2)
out3.shape
(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,  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,  3.3356e-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




```
Pool1 = nn.MaxPool2d((3,3))
out4 = Pool1(out3)
out4.shape
cnn_out = torch.reshape(out4,(1,288,-1))
print(cnn_out.shape)
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],
```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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	$\frac{x_i - \text{mean}(\boldsymbol{x})}{\text{stdev}(\boldsymbol{x})}$
MinMax Scaler	$\frac{x_i - \min(\boldsymbol{x})}{\max(\boldsymbol{x}) - \min(\boldsymbol{x})}$
Robust Scaler	$\frac{x_i - Q_1(\boldsymbol{x})}{Q_3(\boldsymbol{x}) - Q_1(\boldsymbol{x})}$

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)

```python
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)

    ls = []
    pred_list = []
    label_list = []
    val_loss_lst = []
    val_mae_lst = []
    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.float32).to(device)

            space_data = torch.reshape(space_data, (-1,1,11,11 )).to(device)
            space_data = space_data.type(torch.float32)

            label = label.type(torch.float32).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.float32).to(device)
            val_space_data = torch.reshape(val_space_data, (-1,1,11,11 )).to(device)
            val_space_data = val_space_data.type(torch.float32)

            val_label = val_label.type(torch.float32)
            val_pred = model(val_seq, val_space_data).cpu()
```

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5. Test

```python
class myDataset_gru(Dataset):
    def __init__(self, df):

        self.seq_list1 = list(df['Wspd_seq'])
        self.seq_list2 = list(df['Patv_seq'])

        self.seq_list3 = list(df['Etmp_seq'])
        self.seq_list4 = list(df['Itmp_seq'])

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


        self.label_list = df.target.values

    def __getitem__(self, index):

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

        image = np.array(self.seq_list5[index]).astype('float')
        image.resize(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)
```

```python
def pred_gru(model, test_loader,device):
    model.to(device)
    model.eval()

    pred_list = []

    for seq, space_data, label in tqdm(test_loader):
        seq = seq.type(torch.float32).to(device)
        space_data = torch.reshape(space_data, (-1,1,11,11 )).to(device)
        space_data = space_data.type(torch.float32)
        label = label.type(torch.float32).to(device)

        pred = model(seq, space_data)

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

    return pred_list
```

5. Test

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

    os.environ["CUDA_VISIBLE_DEVICES"] = "0"


    test_x = pd.read_csv("train_dataf.csv")
    test_x = test_x.fillna(0)
    test_x = test_x.sort_values(['TurbID','Day','Tmstamp'], ascending=True).reset_index(drop=True)

    model = GRU()

    model.load_state_dict(torch.load('ourbest2batch32shuffleF3sin_data_normal_lr05scaling22yeswspdscale.pdparams'))



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

    df_group = test_x[['Day','Tmstamp','Patv']].groupby(['Day','Tmstamp'], as_index=False).agg(list)
    print(df_group)
    df_group.columns = ['Day','Tmstamp','Patv_list']

    for turbid in range(134):

        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','Tmstamp'])
        turb_data['Patv_space'] = turb_data['Patv_list'].apply(lambda x: [x[i-1] for i in dist_dict[turbid+1][:121]])

        df_test = pd.DataFrame({'Wspd_seq':[list(turb_data['Wspd'])[-144:]],
                               'Patv_seq':[list(turb_data['Patv'])[-144:]],
                               'Etmp_seq':[list(turb_data['Etmp'])[-144:]],
                               'Itmp_seq':[list(turb_data['Itmp'])[-144:]],
                               'Pab1_seq':[list(turb_data['Pab1'])[-144:]],
                                'Patv_space':[list(turb_data['Patv_space'])[-1]],
                               'target': [[0]*288]})

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


    test_dataset = myDataset_gru(test_new)
    test_loader = DataLoader(test_dataset,
                             batch_size=32,
                             shuffle=False,
                             num_workers=0)

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

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