

Deep Autoencoder Neural Networks for Short-Term Traffic Congestion Prediction of Transportation Networks

SEN ZHANG, YONG YAO, JIE HU, YONG ZHAO, SHAOBO LI, JIANJUN HU (2019)

"La **predicción** de la **congestión** es fundamental para implementar sistemas de transporte inteligentes que mejoren la **eficiencia** y la **capacidad** de las **redes de transporte**"

Datos de congestión a gran escala

Datos de congestión a gran escala



Análisis de Imágenes

Datos de congestión a gran escala



Análisis de Imágenes



Predice congestión del tráfico

Presentación del Estudio

Abstract

Introducción

Trabajos Relacionados

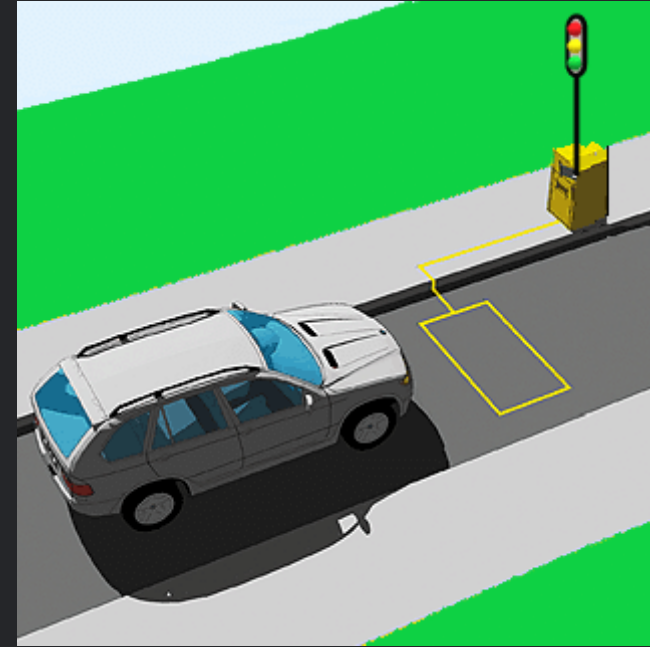
Metodología

Experimentos y Análisis de Resultados

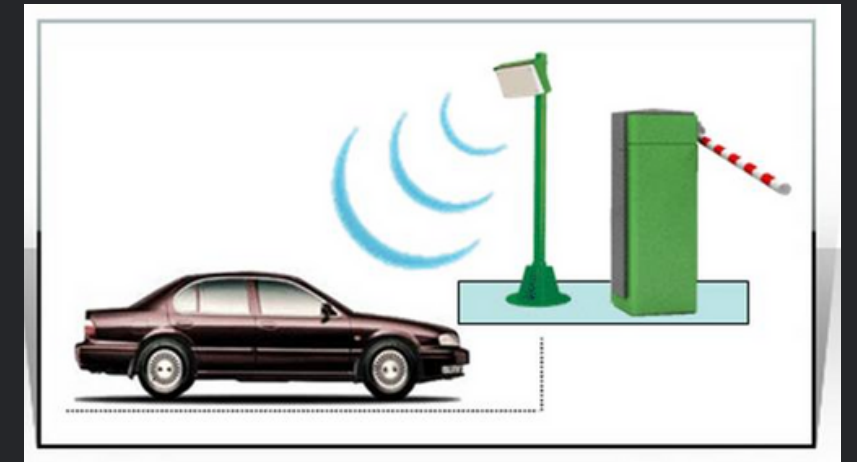
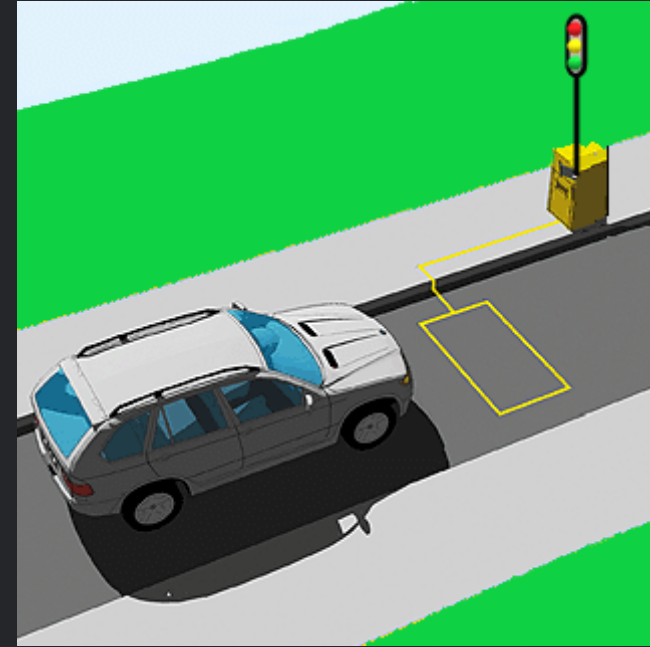
Discusión

Conclusiones

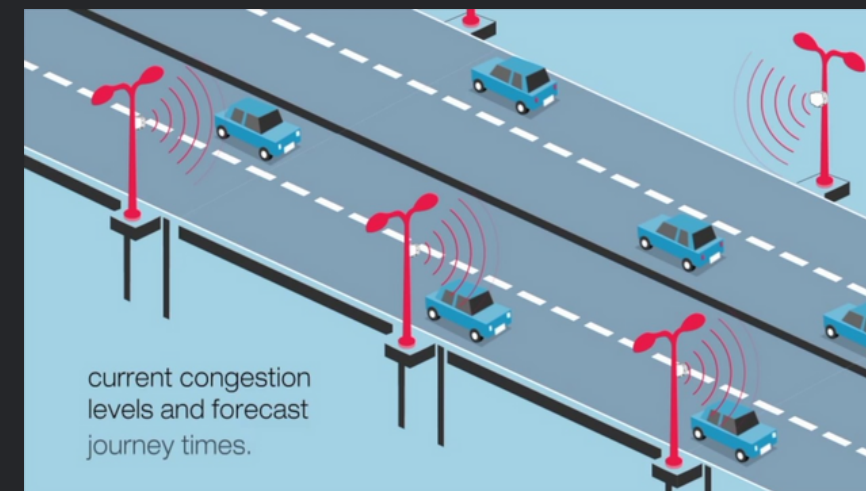
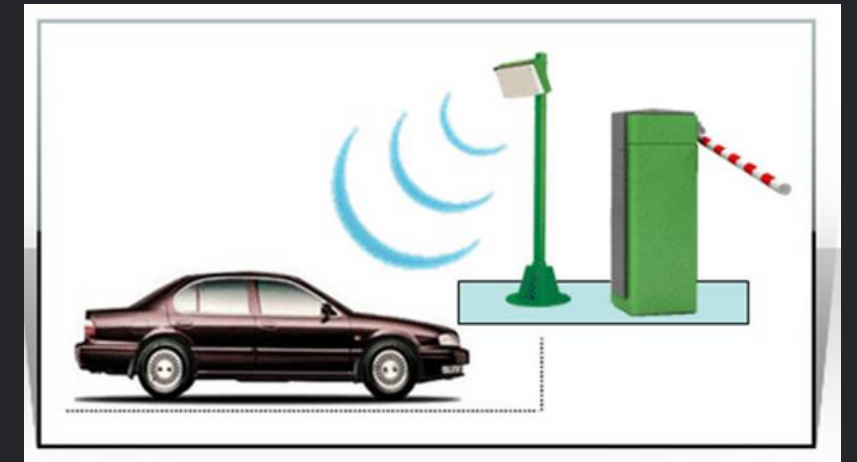
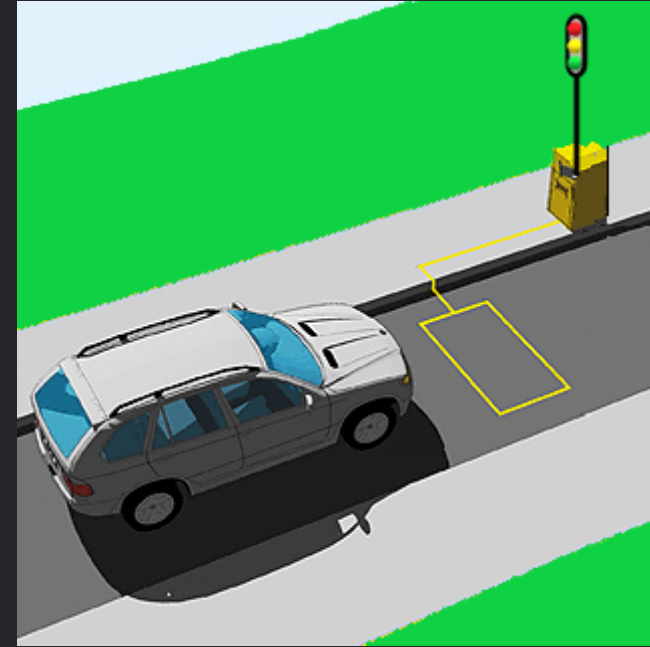
Que
información
se tiene



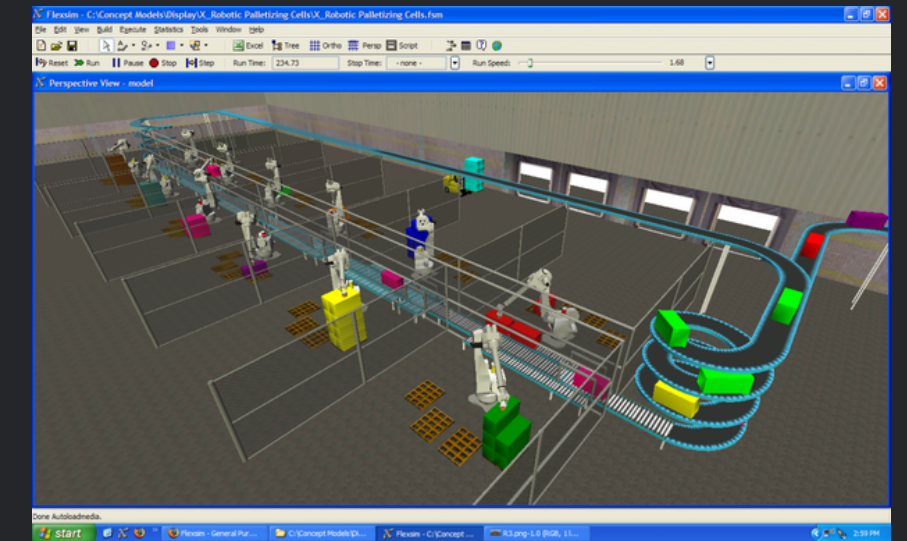
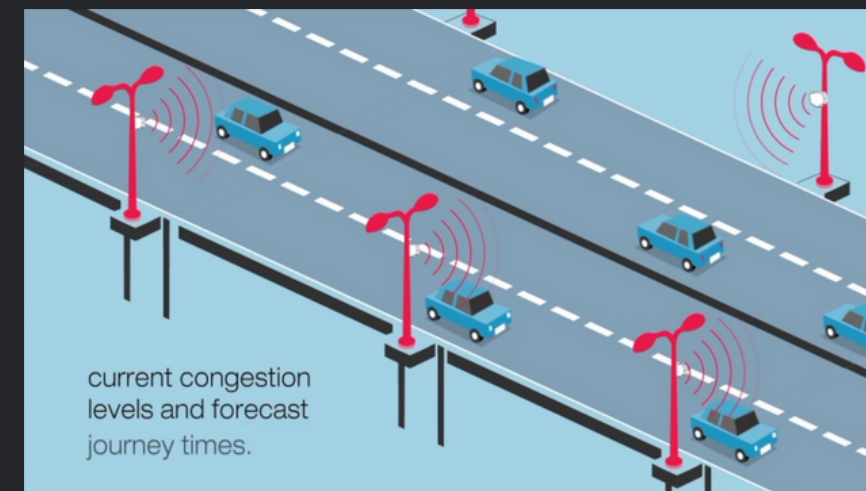
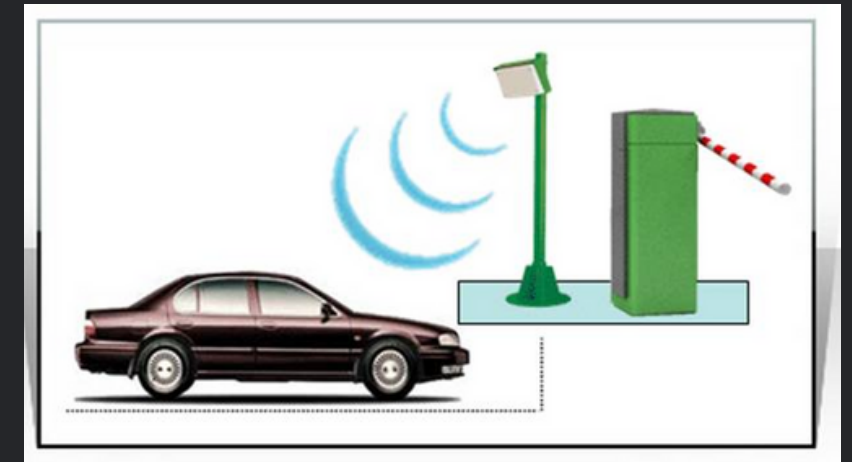
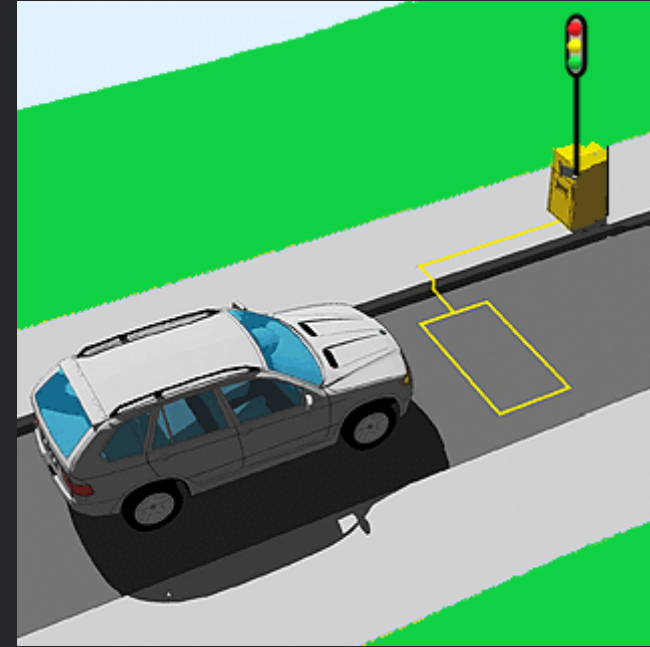
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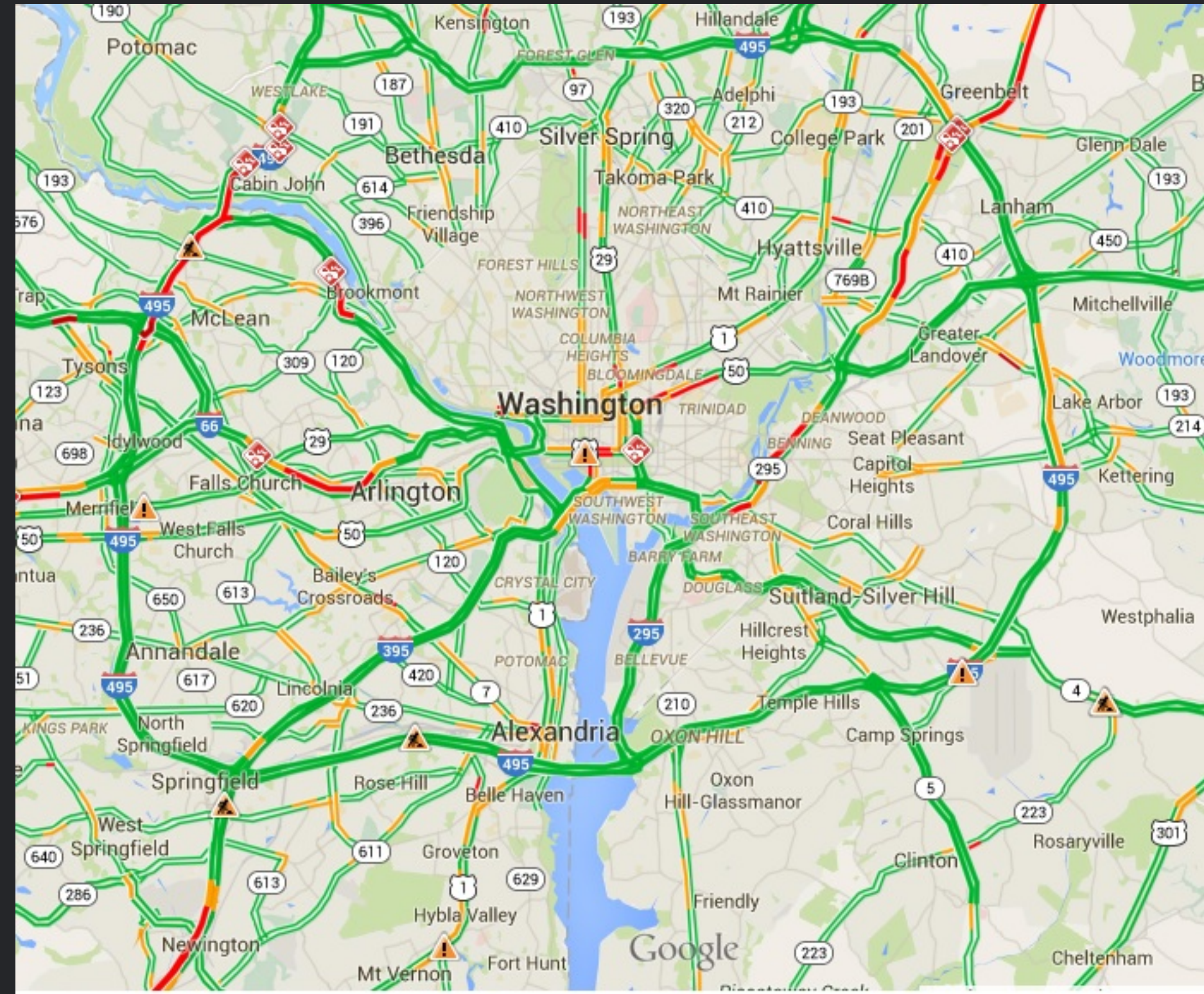
Que información se tiene



Que información se tiene



Que
información
se tiene



Beneficios

Cobertura

Condiciones en tiempo real

Accesibilidad

Otro estudios

ARIMA (series de tiempo, flujos)

SARIMA

KARIMA

ARIMAX

CTM-SARIMA



Acercamientos
Paramétricos

Otro estudios

ARIMA (series de tiempo, flujos)

SARIMA

KARIMA

ARIMAX

CTM-SARIMA



Acercamientos
Paramétricos



Sujetos a estructuras
predeterminadas de modelos

Otro estudios

SVM

Redes Neuronales Artificiales

KNN (velocidades y flujos)

SVM

SVR

Online-SVM



Acercamientos
No Paramétricos

Otro estudios

SVM
Redes Neuronales Artificiales
KNN (velocidades y flujos)
SVM
SVR
Online-SVM



Acercamientos
No Paramétricos



Requieren un conocimiento de dominio
previo significativo y un trabajo de
preprocesamiento extenso

Otro estudios

BIG DATA



RNN

LSTM (flujos, velocidades y
congestión)

CNN

DBN

SRCN

Otro estudios

BIG DATA



RNN

LSTM (flujos, velocidades y congestión)

CNN

DBN

SRCN

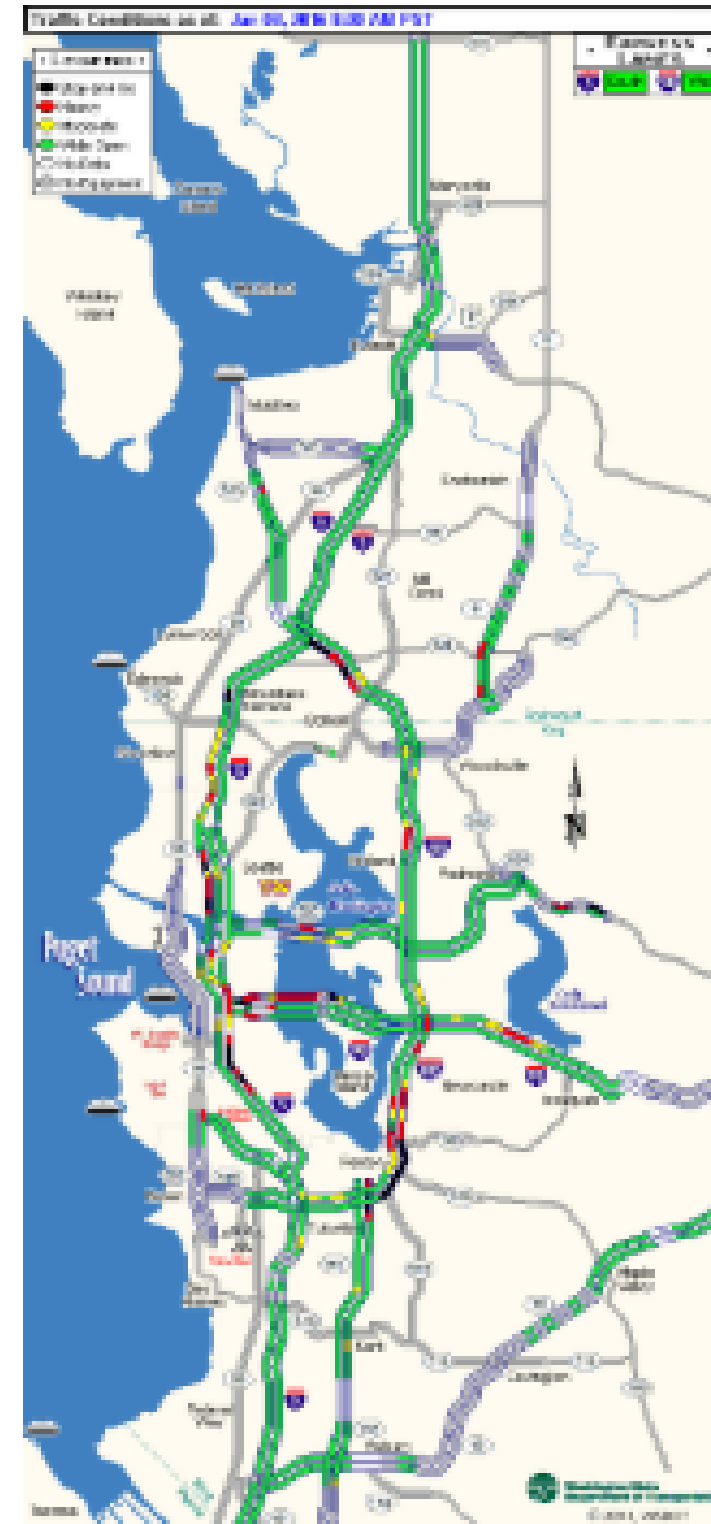


Aprender correlaciones profundas inherentes a los datos con poco o ningún conocimiento previo

"Sin embargo, se siguen enfocando en predicción de variables de tráfico en pequeñas redes"

Metodología

1. Recopilación de imágenes



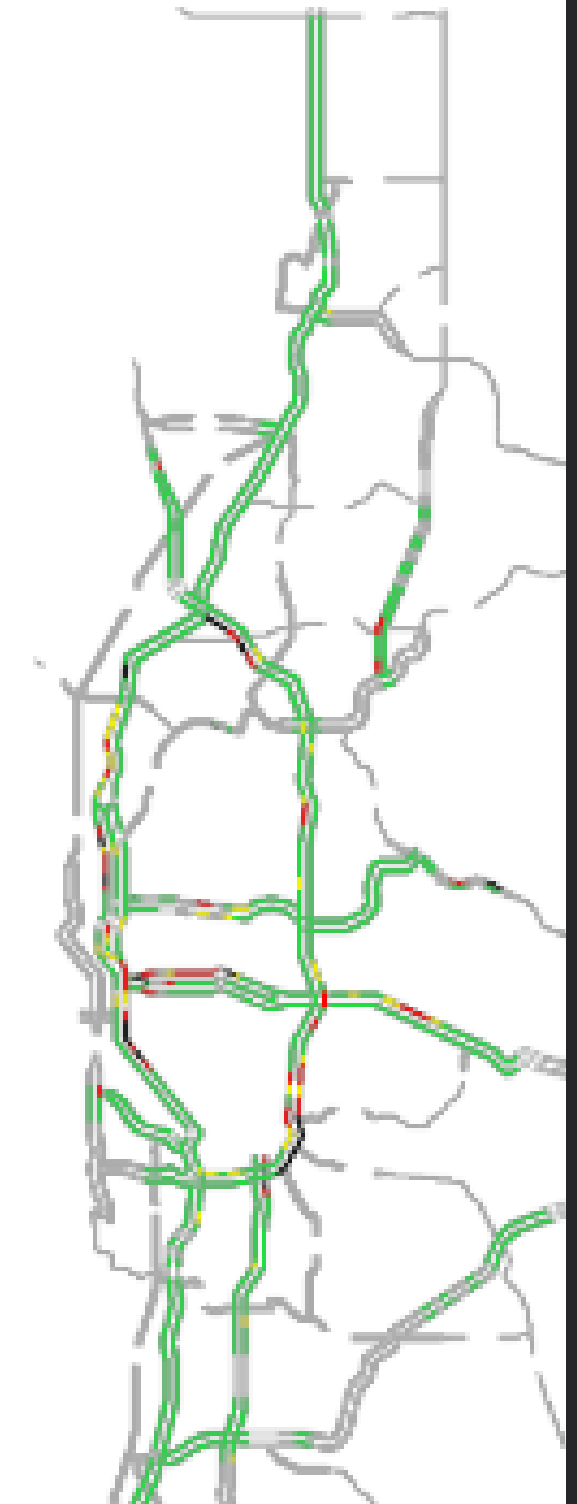
(a)

Metodología

1. Recopilación de imágenes
2. Limpieza de las imágenes



(a)



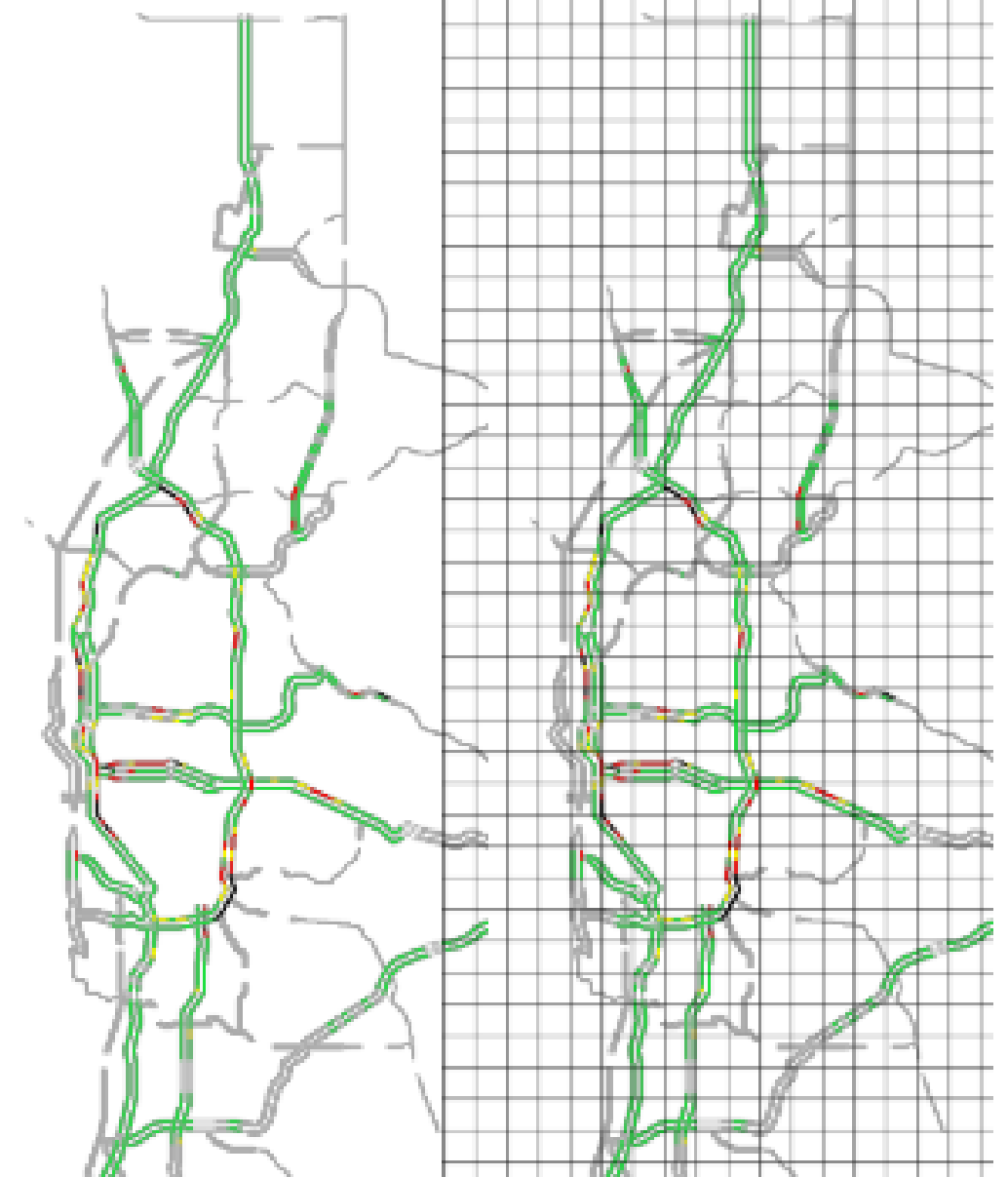
(b)

Metodología

1. Recopilación de imágenes
2. Limpieza de las imágenes
3. División de imágenes en celdas, y a su vez, estas en grillas



(a)

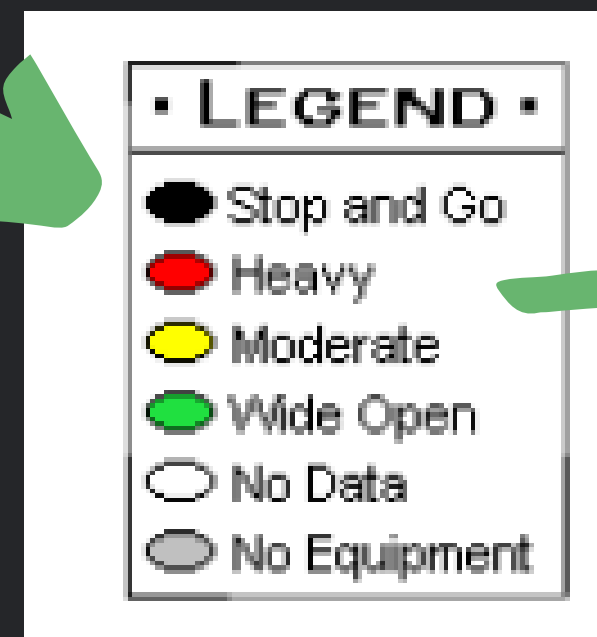
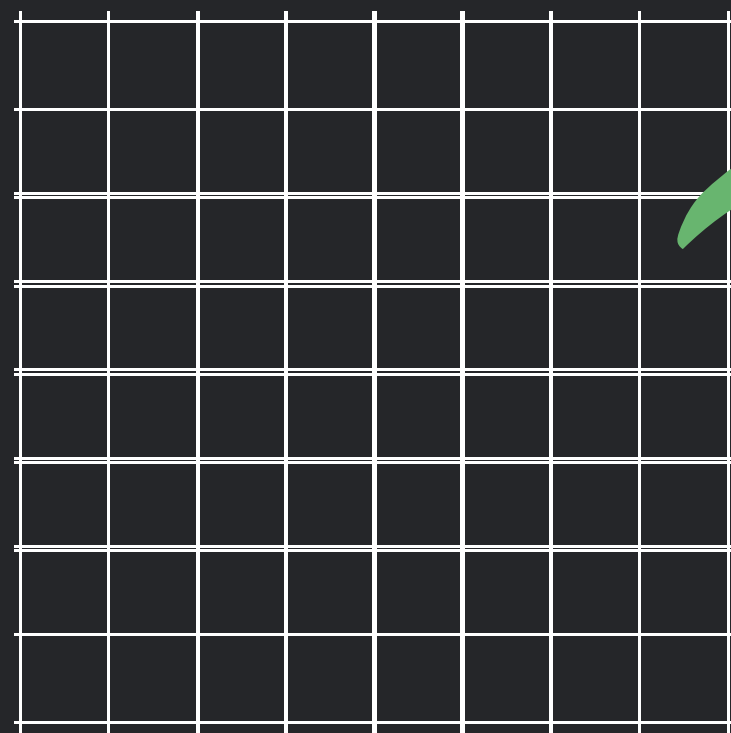


(b)

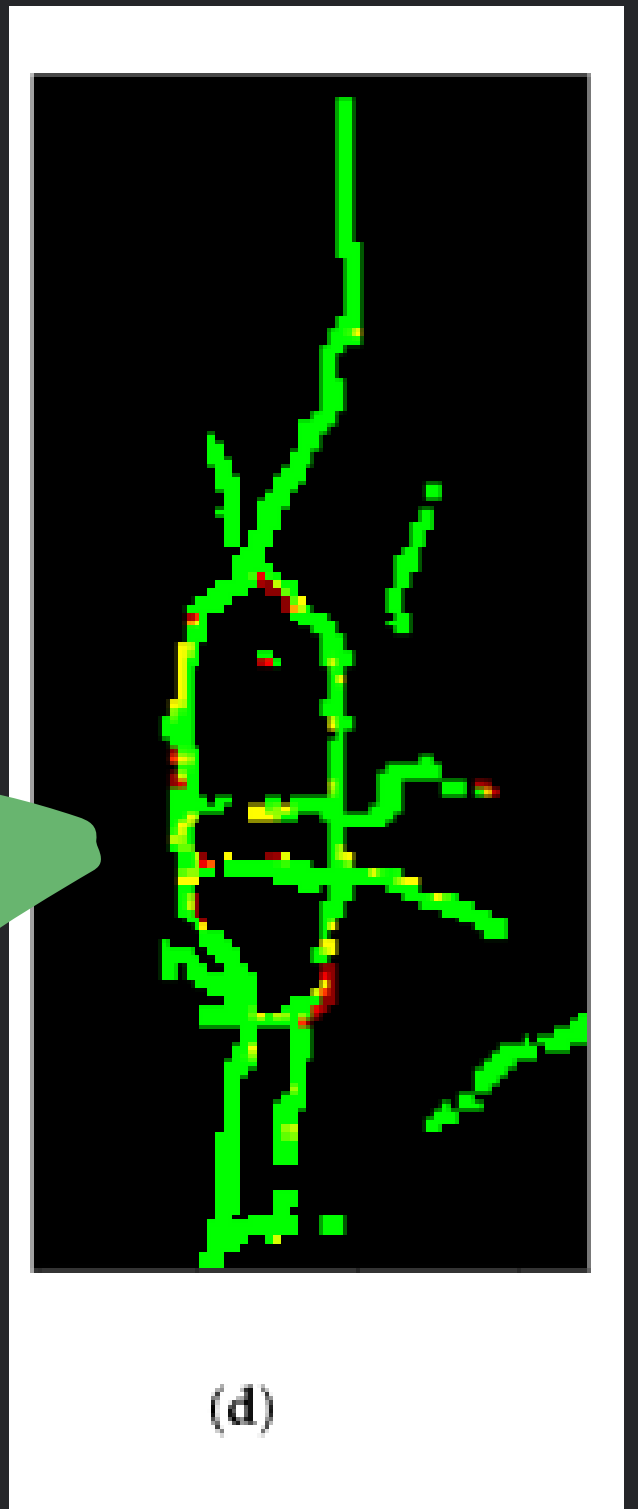
(c)

Metodología

1. Recopilación de imágenes
2. Limpieza de las imágenes
3. División de imágenes en celdas, y a su vez, estas en grillas
4. Cálculo del nivel de congestión por grilla



$$\bar{c}_{i,j}^t = \frac{\sum_{k=1}^{64} c_{t,i,j}^k}{\sum_{k=1}^{64} [c_{t,i,j}^k > 0]}$$



Metodología

1. Recopilación de imágenes
2. Limpieza de las imágenes
3. División de imágenes en celdas, y a su vez, estas en grillas
4. Cálculo del nivel de congestión por grilla
5. Obtención de una matriz representativa

$$R_t = \begin{bmatrix} \bar{c}_{1,1}^t & \bar{c}_{1,2}^t & \dots & \bar{c}_{1,C}^t \\ \bar{c}_{2,1}^t & \bar{c}_{2,2}^t & \dots & \bar{c}_{2,C}^t \\ \vdots & \vdots & \dots & \vdots \\ \bar{c}_{R,1}^t & \bar{c}_{R,2}^t & \dots & \bar{c}_{R,C}^t \end{bmatrix}$$

Problema a Resolver

Series de Tiempo

$(R_{t-n}, \dots, R_{t-2}, R_{t-1}, R_t, R_{t+1}, R_{t+2}, \dots, R_{t+h})$



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Deep Congestion Prediction Network

DPCN - Autoencoder

1. Primera parte

a. Encoder -> Data histórica (4 capas)

b. Decoder -> Representación futura (4 capas)

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a. 2 Capas densas -> Niveles de congestión para gillas

DPCN - Autoencoder

1. Primera parte

- a. Encoder -> Data histórica (4 capas)
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- a. 2 Capas densas -> Niveles de congestión para gillas

3. Se añade una capa de dropout

DPCN - Autoencoder

1. Primera parte

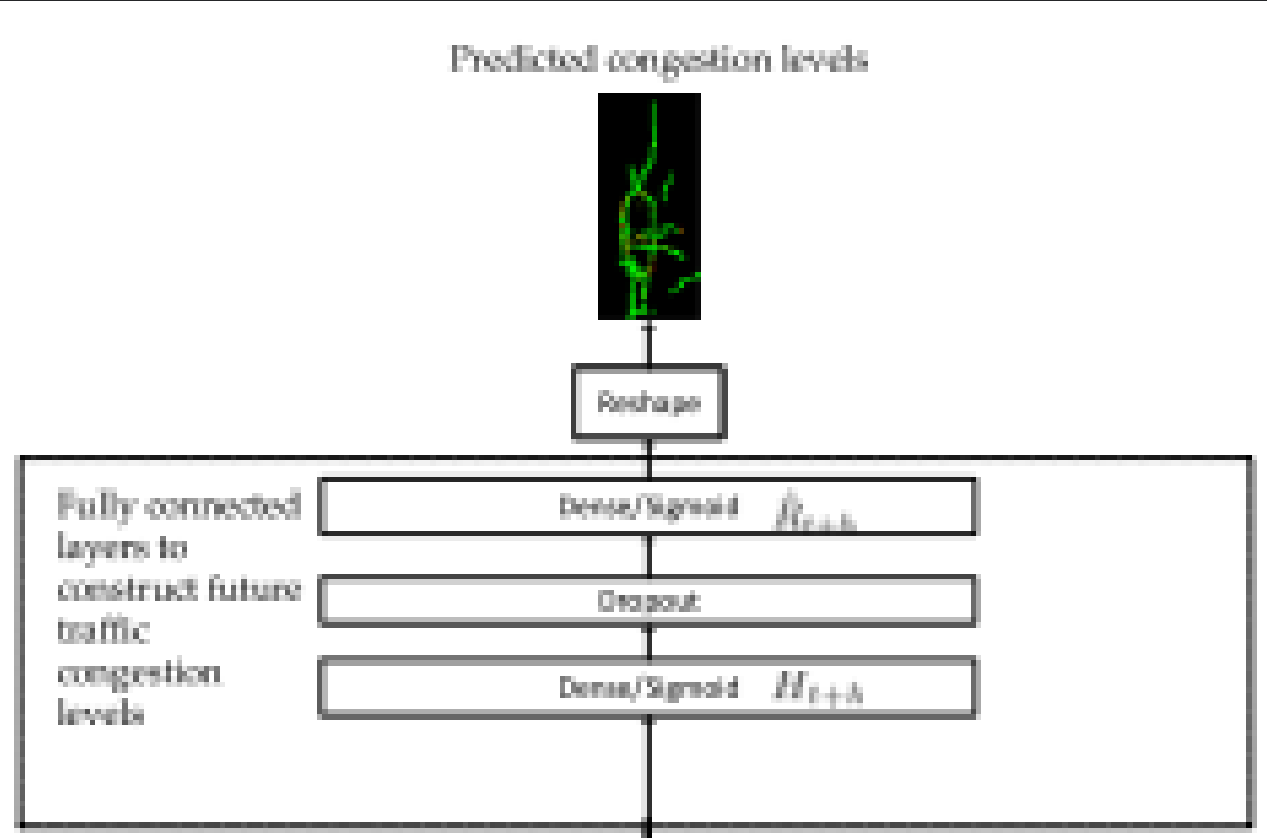
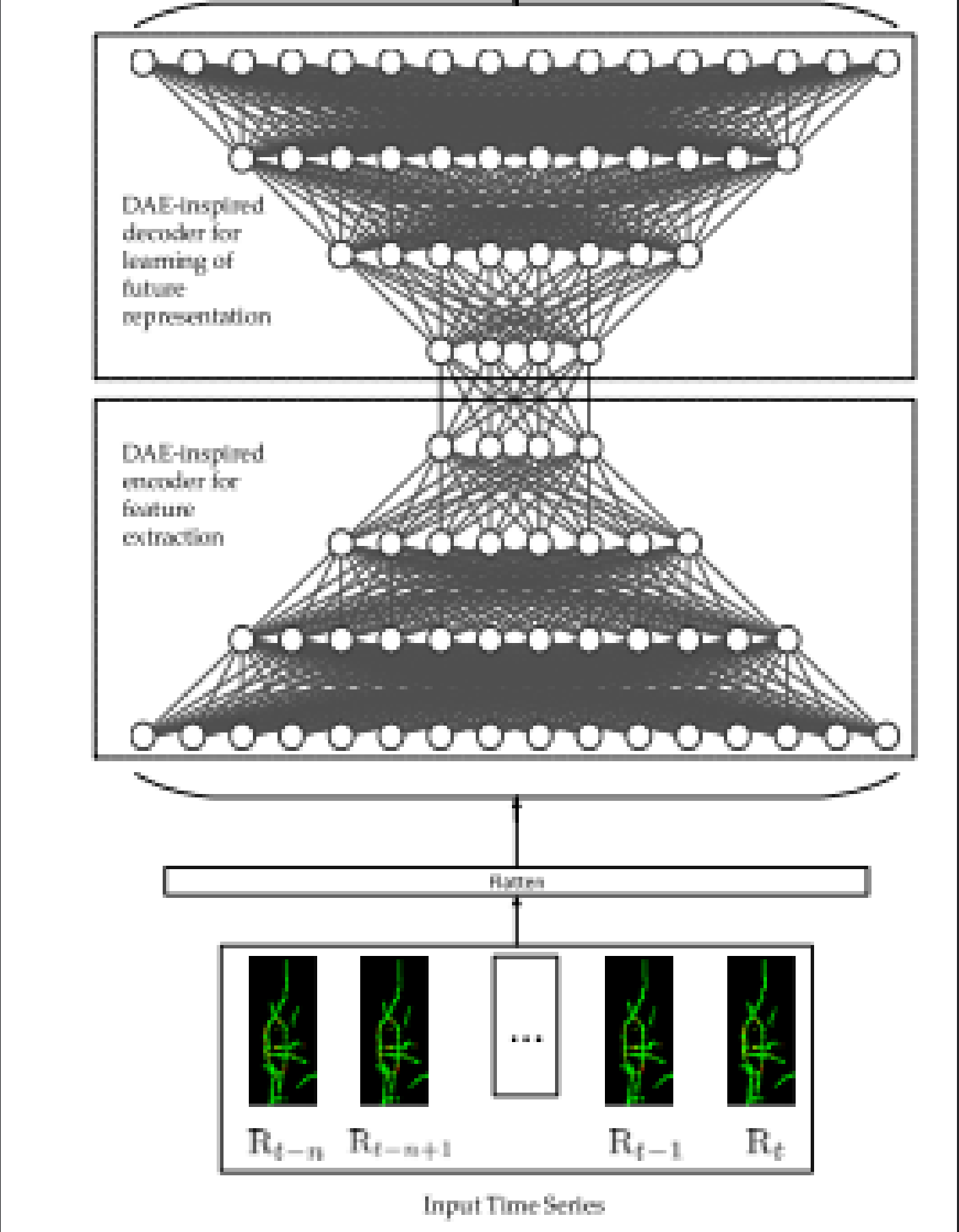
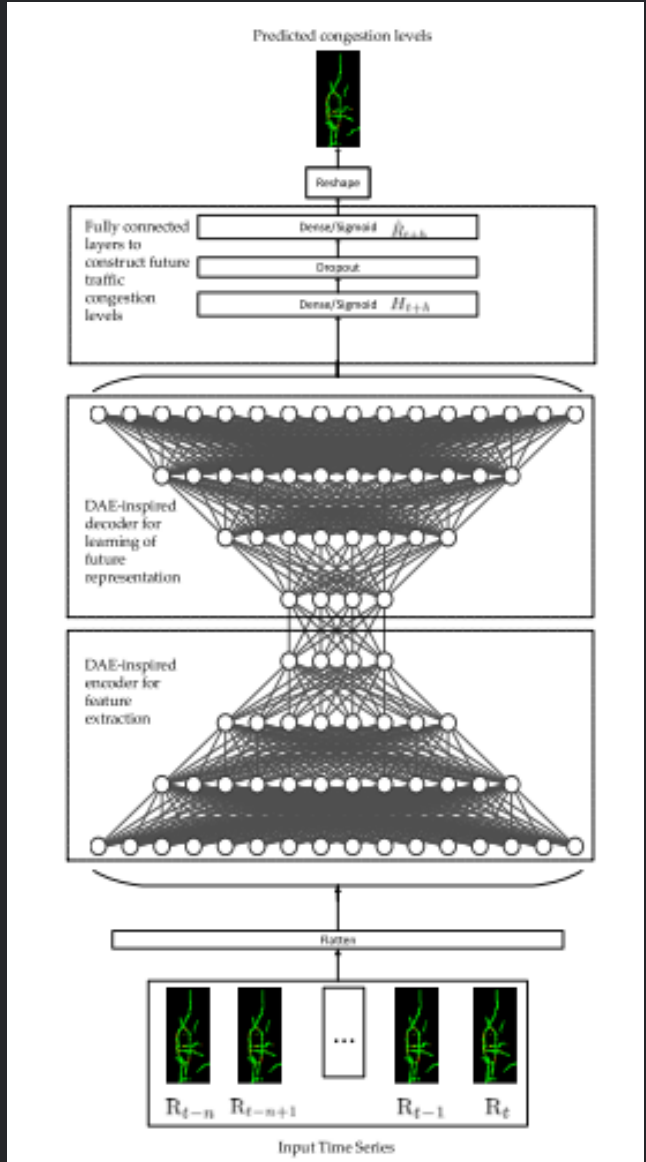
- a. Encoder -> Data histórica (4 capas)
- b. Decoder -> Representación futura (4 capas)

2. Segunda Parte

- a. 2 Capas densas -> Niveles de congestión para gillas

3. Se añade una capa de dropout

4. Capa de reorganización



Características de los Datos

- 07:00 a 10:00 am

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- Días laborales

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- 1-Ene-2016 a 28-Feb-2017

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- 283 días (19 muestras cada uno)
- Intervalos de 10 minutos

Características de los Datos

- 07:00 a 10:00 am
- Días laborales
- Seattle
- 1-Ene-2016 a 28-Feb-2017
- 283 días (19 muestras cada uno)
- Intervalos de 10 minutos
- Datos de 2016 -> Set de entrenamiento
- Datos de 2017 -> Set de testeo via back-testing
- SATCS

Comparación de Modelos

- Comparación con modelos:
 - SRCNN (predicción de velocidades)
 - Uso de capas CNN y LSTM

Comparación de Modelos

- Comparación con modelos:
 - SRCNN (predicción de velocidades)
 - Uso de capas CNN y LSTM
 - ConvLSTM (predicción de tráfico)
 - Múltiples capas ConvLSTM

Comparación de Modelos

- Horizontes Temporales: 10, 30, 60
- Métricas: Mean Absolute Error (MAE) y Weighted Mean Squared Error (wMSE)

Comparación de Modelos

- Horizontes Temporales: 10, 30, 60
- Métricas: Mean Absolute Error (MAE) y Weighted Mean Squared Error (wMSE)

$$MAE = \frac{1}{W \times H} \sum_{i=1}^W \sum_{j=1}^H |c_{ij}^t - \hat{c}_{ij}^t|$$

$$wMSE = \frac{1}{W \times H} \sum_{i=1}^W \sum_{j=1}^H w_{ij}^t \times (c_{ij}^t - \hat{c}_{ij}^t)^2$$

Resultados

Table 1. Comparison of prediction metrics by different configurations of DCPN. Minimum wMSE values marked in bold.

#	Prediction Horizon Averaged Metric Model Config	10 min wMSE	MAE	30 min wMSE	MAE	60 min wMSE	MAE
1st	512_384_256_128	0.058873	0.010635	0.054298	0.010028	0.045638	0.009572
2nd	640_512_384_256	0.058357	0.010737	0.054314	0.010125	0.045414	0.009245
3rd	768_640_512_384	0.061818	0.012796	0.058384	0.012838	0.049112	0.011893
4th	896_768_640_512	0.069279	0.016329	0.064761	0.016280	0.055138	0.016076
5th	1024_896_768_640	0.069227	0.016338	0.064663	0.016229	0.054909	0.015983

Resultados

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5th	1024_896_768_640	0.069227	0.016338	0.064663	0.016229	0.054909	0.015983

Table 2. Significance of difference between the top 2 configurations of DCPN using Welch’s t-test.

Prediction Horizon Averaged Metric Test Results	10 min wMSE	MAE	30 min wMSE	MAE	60 min wMSE	MAE
t stat	0.073076	−0.220181	−0.002431	−0.186772	0.038266	0.734073
p-value	0.941928	0.826291	0.998067	0.852313	0.969571	0.465075

Resultados

Table 3. Comparison of prediction metrics using time lags of 120 and 110 minutes. Minimum wMSE values marked in bold.

Prediction Horizon Averaged Metric Time Lag (minutes)	10 min wMSE	MAE	30 min wMSE	MAE	60 min wMSE	MAE
110	0.058730	0.010705	0.054224	0.010130	0.045305	0.009293
120	0.058873	0.010635	0.054298	0.010028	0.045638	0.009572

Resultados

- Back-Testing para el testeo
 - Series de tiempo
- Error de predicción
 - 2-Ene a 8-Feb (2017)
- 10 minutos de predicción

Resultados

- Back-Testing para el testeo
 - Series de tiempo
- Error de predicción
 - 2-Ene a 8-Feb (2017)
- 10 minutos de predicción
- **DPCN**
 - MAE mejor en 32 días
 - wMSE mejor en 33 días

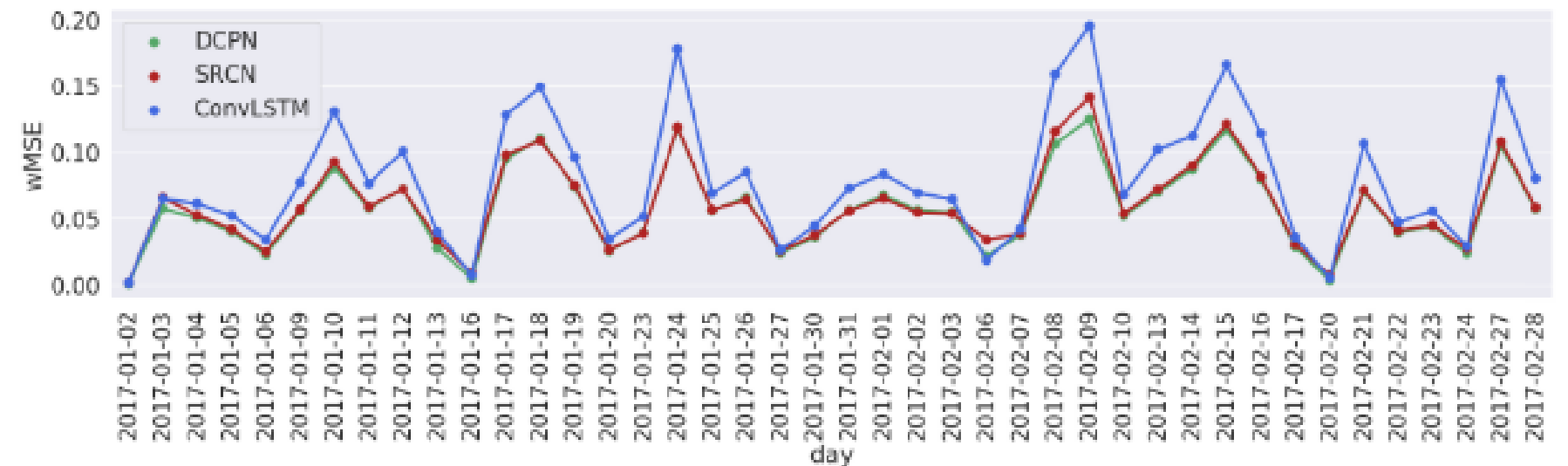


Figure 4. Daily total wMSE errors with a prediction horizon of 10 min on 42 days evaluated with back-testing.

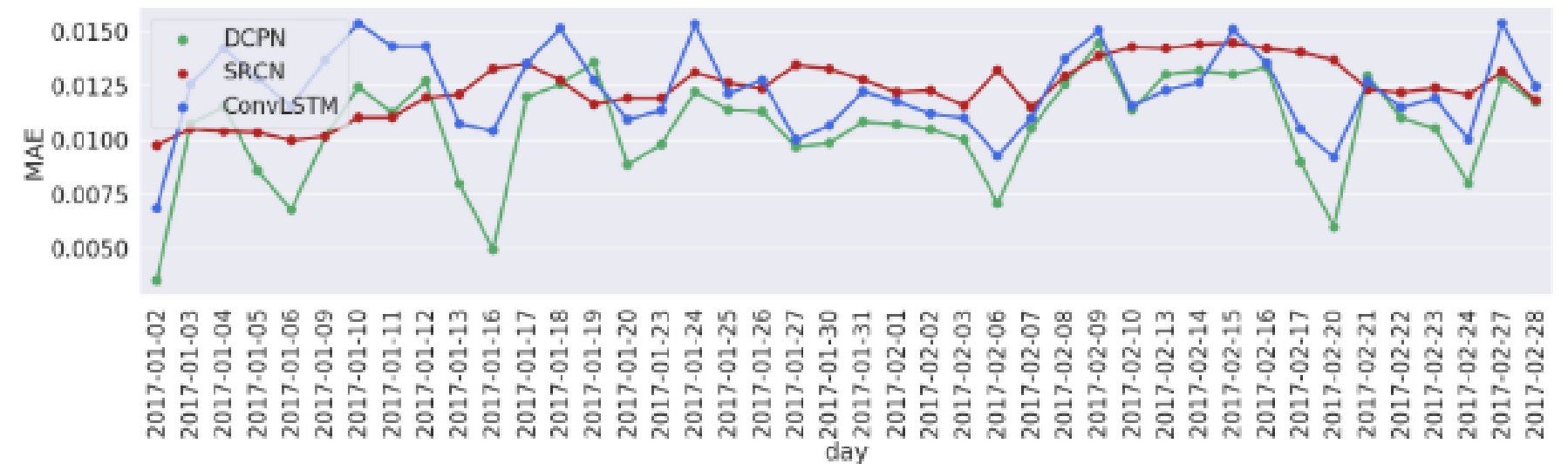


Figure 5. Daily total MAE errors with a prediction horizon of 10 min on 42 days evaluated with back-testing.

Resultados

Table 5. MAE and wMSE by day of the whole network at different prediction horizons of 10, 30, and 60 min through back-testing. Best performance values for each day are marked with a bold typeface.

Day	10 min						30 min						60 min					
	MAE			wMSE			MAE			wMSE			MAE			wMSE		
	SRCN	ConvLSTM	DCPN	SRCN	ConvLSTM	DCPN	SRCN	ConvLSTM	DCPN	SRCN	ConvLSTM	DCPN	SRCN	ConvLSTM	DCPN	SRCN	ConvLSTM	DCPN
2017-01-02	0.0097	0.0068	0.0035	0.0017	0.0016	0.0010	0.0083	0.0069	0.0034	0.0014	0.0016	0.0009	0.0104	0.0072	0.0067	0.0037	0.0023	0.0025
2017-01-03	0.0105	0.0125	0.0107	0.0660	0.0651	0.0576	0.0115	0.0124	0.0109	0.0550	0.0590	0.0543	0.0103	0.0120	0.0088	0.0490	0.0500	0.0483
2017-01-04	0.0104	0.0142	0.0115	0.0527	0.0613	0.0504	0.0103	0.0123	0.0104	0.0460	0.0640	0.0471	0.0093	0.0137	0.0088	0.0387	0.0476	0.0382
2017-01-05	0.0103	0.0128	0.0086	0.0422	0.0525	0.0404	0.0112	0.0127	0.0089	0.0388	0.0491	0.0381	0.0110	0.0149	0.0086	0.0329	0.0405	0.0315
2017-01-06	0.0100	0.0116	0.0068	0.0251	0.0341	0.0228	0.0103	0.0111	0.0071	0.0274	0.0385	0.0234	0.0111	0.0131	0.0077	0.0264	0.0258	0.0214
2017-01-09	0.0102	0.0137	0.0101	0.0571	0.0773	0.0557	0.0110	0.0122	0.0085	0.0577	0.0787	0.0531	0.0120	0.0128	0.0093	0.0516	0.0538	0.0447
2017-01-10	0.0110	0.0154	0.0124	0.0927	0.1307	0.0881	0.0158	0.0141	0.0118	0.1051	0.1302	0.0814	0.0127	0.0146	0.0115	0.0917	0.1057	0.0676
2017-01-11	0.0110	0.0143	0.0112	0.0593	0.0765	0.0582	0.0167	0.0121	0.0108	0.0704	0.0795	0.0508	0.0108	0.0138	0.0111	0.0468	0.0534	0.0395
2017-01-12	0.0119	0.0143	0.0127	0.0722	0.1010	0.0725	0.0130	0.0146	0.0124	0.0900	0.1122	0.0724	0.0115	0.0131	0.0117	0.0812	0.0879	0.0683
2017-01-13	0.0121	0.0107	0.0080	0.0337	0.0399	0.0277	0.0100	0.0113	0.0087	0.0364	0.0375	0.0259	0.0103	0.0140	0.0081	0.0385	0.0391	0.0285
2017-01-16	0.0133	0.0104	0.0049	0.0089	0.0075	0.0050	0.0107	0.0093	0.0058	0.0089	0.0064	0.0048	0.0097	0.0122	0.0044	0.0067	0.0087	0.0036
2017-01-17	0.0135	0.0135	0.0120	0.0981	0.1282	0.0951	0.0124	0.0132	0.0118	0.1118	0.1262	0.0912	0.0110	0.0128	0.0106	0.0907	0.0983	0.0752
2017-01-18	0.0127	0.0151	0.0126	0.1089	0.1495	0.1106	0.0132	0.0162	0.0122	0.1318	0.1621	0.1024	0.0134	0.0142	0.0107	0.1169	0.1243	0.0866
2017-01-19	0.0116	0.0127	0.0136	0.0750	0.0965	0.0738	0.0110	0.0132	0.0112	0.0807	0.0943	0.0665	0.0112	0.0124	0.0094	0.0679	0.0755	0.0533
2017-01-20	0.0119	0.0109	0.0088	0.0263	0.0346	0.0255	0.0079	0.0124	0.0083	0.0292	0.0308	0.0257	0.0072	0.0108	0.0085	0.0208	0.0242	0.0179
2017-01-23	0.0119	0.0114	0.0098	0.0391	0.0517	0.0396	0.0094	0.0120	0.0098	0.0455	0.0519	0.0375	0.0079	0.0108	0.0088	0.0314	0.0337	0.0264
2017-01-24	0.0131	0.0153	0.0122	0.1191	0.1780	0.1182	0.0131	0.0146	0.0136	0.1330	0.1735	0.1118	0.0114	0.0141	0.0117	0.1261	0.1262	0.0850
2017-01-25	0.0126	0.0121	0.0114	0.0568	0.0693	0.0563	0.0097	0.0124	0.0123	0.0614	0.0691	0.0546	0.0082	0.0115	0.0092	0.0480	0.0512	0.0397
2017-01-26	0.0124	0.0127	0.0113	0.0642	0.0851	0.0658	0.0100	0.0122	0.0108	0.0697	0.0884	0.0605	0.0093	0.0118	0.0090	0.0578	0.0595	0.0433
2017-01-27	0.0135	0.0100	0.0097	0.0255	0.0264	0.0240	0.0079	0.0099	0.0082	0.0243	0.0300	0.0219	0.0079	0.0105	0.0075	0.0242	0.0253	0.0187
2017-01-30	0.0133	0.0107	0.0099	0.0377	0.0445	0.0363	0.0085	0.0105	0.0094	0.0312	0.0399	0.0310	0.0079	0.0103	0.0073	0.0262	0.0281	0.0224
2017-01-31	0.0128	0.0122	0.0108	0.0560	0.0731	0.0565	0.0093	0.0111	0.0107	0.0598	0.0693	0.0493	0.0073	0.0097	0.0085	0.0450	0.0527	0.0403
2017-02-01	0.0122	0.0118	0.0107	0.0634	0.0838	0.0675	0.0105	0.0116	0.0105	0.0723	0.0901	0.0619	0.0086	0.0109	0.0099	0.0618	0.0685	0.0500
2017-02-02	0.0123	0.0112	0.0105	0.0547	0.0694	0.0564	0.0095	0.0112	0.0105	0.0582	0.0662	0.0518	0.0085	0.0113	0.0093	0.0484	0.0502	0.0408
2017-02-03	0.0116	0.0110	0.0100	0.0539	0.0645	0.0548	0.0095	0.0107	0.0100	0.0550	0.0618	0.0469	0.0084	0.0103	0.0079	0.0401	0.0408	0.0331
2017-02-06	0.0132	0.0093	0.0071	0.0340	0.0185	0.0217	0.0123	0.0095	0.0097	0.0212	0.0189	0.0108	0.0127	0.0134	0.0061	0.0225	0.0308	0.0208
2017-02-07	0.0115	0.0110	0.0105	0.0390	0.0424	0.0380	0.0096	0.0102	0.0079	0.0361	0.0391	0.0324	0.0096	0.0106	0.0074	0.0299	0.0307	0.0245
2017-02-08	0.0129	0.0137	0.0126	0.1159	0.1591	0.1064	0.0121	0.0142	0.0125	0.1313	0.1812	0.1046	0.0113	0.0133	0.0122	0.1333	0.1674	0.0943
2017-02-09	0.0139	0.0150	0.0144	0.1417	0.1955	0.1251	0.0136	0.0157	0.0133	0.1562	0.2183	0.1221	0.0130	0.0139	0.0123	0.1464	0.1698	0.1097
2017-02-10	0.0143	0.0116	0.0114	0.0538	0.0679	0.0522	0.0103	0.0120	0.0105	0.0576	0.0718	0.0488	0.0090	0.0111	0.0101	0.0472	0.0546	0.0411
2017-02-13	0.0142	0.0123	0.0130	0.0722	0.1023	0.0702	0.0110	0.0124	0.0122	0.0809	0.0949	0.0612	0.0095	0.0118	0.0117	0.0694	0.0795	0.0532
2017-02-14	0.0144	0.0126	0.0132	0.0901	0.1123	0.0873	0.0122	0.0133	0.0134	0.1054	0.1381	0.0891	0.0112	0.0120	0.0115	0.1011	0.1137	0.0815
2017-02-15	0.0145	0.0151	0.0130	0.1214	0.1660	0.1173	0.0142	0.0152	0.0124	0.1366	0.1676	0.1099	0.0125	0.0141	0.0120	0.1213	0.1428	0.0943
2017-02-16	0.0142	0.0135	0.0134	0.0817	0.1144	0.0802	0.0118	0.0135	0.0116	0.0888	0.1150	0.0733	0.0100	0.0124	0.0112	0.0783	0.0895	0.0643
2017-02-17	0.0140	0.0105	0.0090	0.0306	0.0360	0.0288	0.0074	0.0101	0.0083	0.0308	0.0340	0.0265	0.0072	0.0100	0.0089	0.0289	0.0301	0.0244
2017-02-20	0.0137	0.0092	0.0060	0.0074	0.0052	0.0034	0.0101	0.0091	0.0049	0.0065	0.0070	0.0041	0.0112	0.0116	0.0060	0.0083	0.0096	0.0048
2017-02-21	0.0123	0.0127	0.0129	0.0716	0.1065	0.0707	0.0101	0.0125	0.0111	0.0769	0.1067	0.0640	0.0090	0.0109	0.0108	0.0630	0.0785	0.0515
2017-02-22	0.0122	0.0115	0.0110	0.0410	0.0472	0.0396	0.0094	0.0113	0.0096	0.0435	0.0519	0.0341	0.0078	0.0107	0.0089	0.0307	0.0363	0.0274
2017-02-23	0.0124	0.0119	0.0105	0.0451	0.0558	0.0443	0.0097	0.0114	0.0094	0.0435	0.0513	0.0365	0.0075	0.0102	0.0082	0.0306	0.0348	0.0269
2017-02-24	0.0121	0.0100	0.0080	0.0274	0.0291	0.0236	0.0081	0.0097	0.0085	0.0249	0.0308	0.0218	0.0075	0.0096	0.0113	0.0195	0.0235	0.0206
2017-02-27	0.0132	0.0154	0.0128	0.1078	0.1547	0.1051	0.0127	0.0166	0.0120	0.1142	0.1672	0.0937	0.0110	0.0134	0.0119	0.0910	0.1231	0.0753
2017-02-28	0.0118	0.0125	0.0117	0.0586	0.0804	0.0576	0.0096	0.0120	0.0113	0.0606	0.0800	0.0522	0.0082	0.0111	0.0118	0.0485	0.0604	0.0427

Resultados

MAE		
Tiempo	SRCN	DPCN
30 minutos	22	20
60 minutos	21	21
wMSE		
Tiempo	-	DPCN
30 minutos	-	41
60 minutos	-	40

- Promedios mas bajos para MAE y wMSE para 10, 30 y 60 minutos

Table 5. MAE and wMSE by day of the whole network at different prediction horizons of 10, 30, and 60 min through back-testing. Best performance values for each day are marked with a bold typeface.

Day	10 min						30 min						60 min					
	MAE			wMSE			MAE			wMSE			MAE			wMSE		
	SRCN	ConvLSTM	DCPN	SRCN	ConvLSTM	DCPN	SRCN	ConvLSTM	DCPN	SRCN	ConvLSTM	DCPN	SRCN	ConvLSTM	DCPN	SRCN	ConvLSTM	DCPN
2017-01-02	0.0097	0.0068	0.0035	0.0017	0.0016	0.0010	0.0083	0.0069	0.0034	0.0014	0.0016	0.0009	0.0104	0.0072	0.0067	0.0037	0.0023	0.0025
2017-01-03	0.0105	0.0125	0.0107	0.0660	0.0651	0.0576	0.0115	0.0124	0.0109	0.0550	0.0590	0.0543	0.0103	0.0120	0.0088	0.0490	0.0500	0.0483
2017-01-04	0.0104	0.0142	0.0115	0.0527	0.0613	0.0504	0.0103	0.0123	0.0104	0.0460	0.0640	0.0471	0.0093	0.0137	0.0088	0.0387	0.0476	0.0382
2017-01-05	0.0103	0.0128	0.0086	0.0422	0.0525	0.0404	0.0112	0.0127	0.0089	0.0388	0.0491	0.0381	0.0110	0.0149	0.0086	0.0329	0.0405	0.0315
2017-01-06	0.0100	0.0116	0.0068	0.0251	0.0341	0.0228	0.0103	0.0111	0.0071	0.0274	0.0385	0.0234	0.0111	0.0131	0.0077	0.0264	0.0258	0.0214
2017-01-09	0.0102	0.0137	0.0101	0.0571	0.0773	0.0557	0.0110	0.0122	0.0085	0.0577	0.0787	0.0531	0.0120	0.0128	0.0093	0.0516	0.0538	0.0447
2017-01-10	0.0110	0.0154	0.0124	0.0927	0.1307	0.0881	0.0158	0.0141	0.0118	0.1051	0.1302	0.0814	0.0127	0.0146	0.0115	0.0917	0.1057	0.0676
2017-01-11	0.0110	0.0143	0.0112	0.0593	0.0765	0.0582	0.0167	0.0121	0.0108	0.0704	0.0795	0.0508	0.0108	0.0138	0.0111	0.0468	0.0534	0.0395
2017-01-12	0.0119	0.0143	0.0127	0.0722	0.1010	0.0725	0.0130	0.0146	0.0124	0.0900	0.1122	0.0724	0.0115	0.0131	0.0117	0.0812	0.0879	0.0683
2017-01-13	0.0121	0.0107	0.0080	0.0337	0.0399	0.0277	0.0100	0.0113	0.0087	0.0364	0.0375	0.0259	0.0103	0.0140	0.0081	0.0385	0.0391	0.0285
2017-01-16	0.0133	0.0104	0.0049	0.0089	0.0075	0.0050	0.0107	0.0093	0.0058	0.0089	0.0064	0.0048	0.0097	0.0122	0.0044	0.0067	0.0087	0.0036
2017-01-17	0.0135	0.0135	0.0120	0.0981	0.1282	0.0951	0.0124	0.0132	0.0118	0.1118	0.1262	0.0912	0.0110	0.0128	0.0106	0.0907	0.0983	0.0752
2017-01-18	0.0127	0.0151	0.0126	0.1089	0.1495	0.1106	0.0132	0.0162	0.0122	0.1318	0.1621	0.1024	0.0134	0.0142	0.0107	0.1169	0.1243	0.0866
2017-01-19	0.0116	0.0127	0.0136	0.0750	0.0965	0.0738	0.0110	0.0132	0.0112	0.0807	0.0943	0.0665	0.0112	0.0124	0.0094	0.0679	0.0755	0.0533
2017-01-20	0.0119	0.0109	0.0088	0.0263	0.0346	0.0255	0.0079	0.0124	0.0083	0.0292	0.0308	0.0257	0.0072	0.0108	0.0085	0.0208	0.0242	0.0179
2017-01-23	0.0119	0.0114	0.0098	0.0391	0.0517	0.0396	0.0094	0.0120	0.0098	0.0455	0.0519	0.0375	0.0079	0.0108	0.0088	0.0314	0.0337	0.0264
2017-01-24	0.0131	0.0153	0.0122	0.1191	0.1780	0.1182	0.0131	0.0146	0.0136	0.1330	0.1735	0.1118	0.0114	0.0141	0.0117	0.1261	0.1262	0.0850
2017-01-25	0.0126	0.0121	0.0114	0.0568	0.0693	0.0563	0.0097	0.0124	0.0123	0.0614	0.0691	0.0546	0.0082	0.0115	0.0092	0.0480	0.0512	0.0397
2017-01-26	0.0124	0.0127	0.0113	0.0642	0.0851	0.0658	0.0100	0.0122	0.0108	0.0697	0.0884	0.0605	0.0093	0.0118	0.0090	0.0578	0.0595	0.0433
2017-01-27	0.0135	0.0100	0.0097	0.0255	0.0264	0.0240	0.0079	0.0099	0.0082	0.0243	0.0300	0.0219	0.0079	0.0105	0.0075	0.0242	0.0253	0.0187
2017-01-30	0.0133	0.0107	0.0099	0.0377	0.0445	0.0363	0.0085	0.0105	0.0094	0.0312	0.0399	0.0310	0.0079	0.0103	0.0073	0.0262	0.0281	0.0224
2017-01-31	0.0128	0.0122	0.0108	0.0560	0.0731	0.0565	0.0093	0.0111	0.0107	0.0598	0.0693	0.0493	0.0073	0.0097	0.0085	0.0450	0.0527	0.0403
2017-02-01	0.0122	0.0118	0.0107	0.0654	0.0838	0.0675	0.0105	0.0116	0.0105	0.0723	0.0901	0.0619	0.0086	0.0109	0.0099	0.0618	0.0685	0.0500
2017-02-02	0.0123	0.0112	0.0105	0.0547	0.0694	0.0564	0.0095	0.0112	0.0105	0.0582	0.0662	0.0518	0.0085	0.0113	0.0093	0.0484	0.0502	0.0408
2017-02-03	0.0116	0.0110	0.0100	0.0539	0.0645	0.0548	0.0095	0.0107	0.0100	0.0550	0.0618	0.0469	0.0084	0.0103	0.0079	0.0401	0.0408	0.0331
2017-02-06	0.0132	0.0093	0.0071	0.0340	0.0185	0.0217	0.0123	0.0095	0.0097	0.0212	0.0189	0.0108	0.0127	0.0134	0.0061	0.0225	0.0308	0.0208
2017-02-07	0.0115	0.0110	0.0105	0.0390	0.0424	0.0380	0.0096	0.0102	0.0079	0.0361	0.0391	0.0324	0.0096	0.0106	0.0074	0.0299	0.0307	0.0245
2017-02-08	0.0129	0.0137	0.0126	0.1159	0.1591	0.1064	0.0121	0.0142	0.0125	0.1313	0.1812	0.1046	0.0113	0.0133	0.0122	0.1333	0.1674	0.0943
2017-02-09	0.0139	0.0150	0.0144	0.1417	0.1955	0.1251	0.0136	0.0157	0.0133	0.1562	0.2183	0.1221	0.0130	0.0139	0.0123	0.1464	0.1698	0.1097
2017-02-10	0.0143	0.0116	0.0114	0.0538	0.0679	0.0522	0.0103	0.0120	0.0105	0.0576	0.0718	0.0488	0.0090	0.0111	0.0101	0.0472	0.0546	0.0411
2017-02-13	0.0142	0.0123	0.0130	0.0722	0.1023	0.0702	0.0110	0.0124	0.0122	0.0809	0.0949	0.0612	0.0095	0.0118	0.0117	0.0694	0.0795	0.0532
2017-02-14	0.0144	0.0126	0.0132	0.0901	0.1123	0.0873	0.0122	0.0133	0.0134	0.1054	0.1381	0.0891	0.0112	0.0120	0.0115	0.1011	0.1137	0.0815
2017-02-15	0.0145	0.0151	0.0130	0.1214	0.1660	0.1173	0.0142	0.0152	0.0124	0.1366	0.1676	0.1099	0.0125	0.0141	0.0120	0.1213	0.1428	0.0943
2017-02-16	0.0142	0.0135	0.0134	0.0817	0.1144	0.0802	0.0118	0.0135	0.0116	0.0888	0.1150	0.0733	0.0100	0.0124	0.0112	0.0783	0.0895	0.0643
2017-02-17	0.0140	0.0105	0.0090	0.0306	0.0360	0.0288	0.0074	0.0101	0.0083	0.0308	0.0340	0.0265	0.0072	0.0100	0.0089	0.0289	0.0301	0.0244
2017-02-20	0.0137	0.0092	0.0060	0.0074	0.0052	0.0034	0.0101	0.0091	0.0049	0.0065	0.0070	0.0041	0.0112	0.0116	0.0060	0.0083	0.0096	0.0048
2017-02-21	0.0123	0.0127	0.0129	0.0716	0.1065	0.0707	0.0101	0.0125	0.0111	0.0769	0.1067	0.0640	0.0090	0.0109	0.0108	0.0630	0.0785	0.0515
2017-02-22	0.0122	0.0115	0.0110	0.0410	0.0472	0.0396	0.0094	0.0113	0.0096	0.0435	0.0519	0.0341	0.0078	0.0107	0.0089	0.0307	0.0363	0.0274
2017-02-23	0.0124	0.0119	0.0105	0.0451	0.0558	0.0443	0.0097	0.0114	0.0094	0.0435	0.0513	0.0365	0.0075	0.0102	0.0082	0.0306	0.0348	0.0269
2017-02-24	0.0121	0.0100	0.0080	0.0274	0.0291	0.0236	0.0081	0.0097	0.0085	0.0249	0.0308	0.0218	0.0075	0.0096	0.0113	0.0195	0.0235	0.0206
2017-02-27	0.0132	0.0154	0.0128	0.1078	0.1547	0.1051	0.0127	0.0166	0.0120	0.1142	0.1672	0.0937	0.0110	0.0134	0.0119	0.0910	0.1231	0.0753
2017-02-28	0.0118	0.0125	0.0117	0.0586	0.0804	0.0576	0.0096	0.0120	0.0113	0.0606	0.0800	0.0522	0.0082	0.0111	0.0118	0.0485	0.0604	0.0427

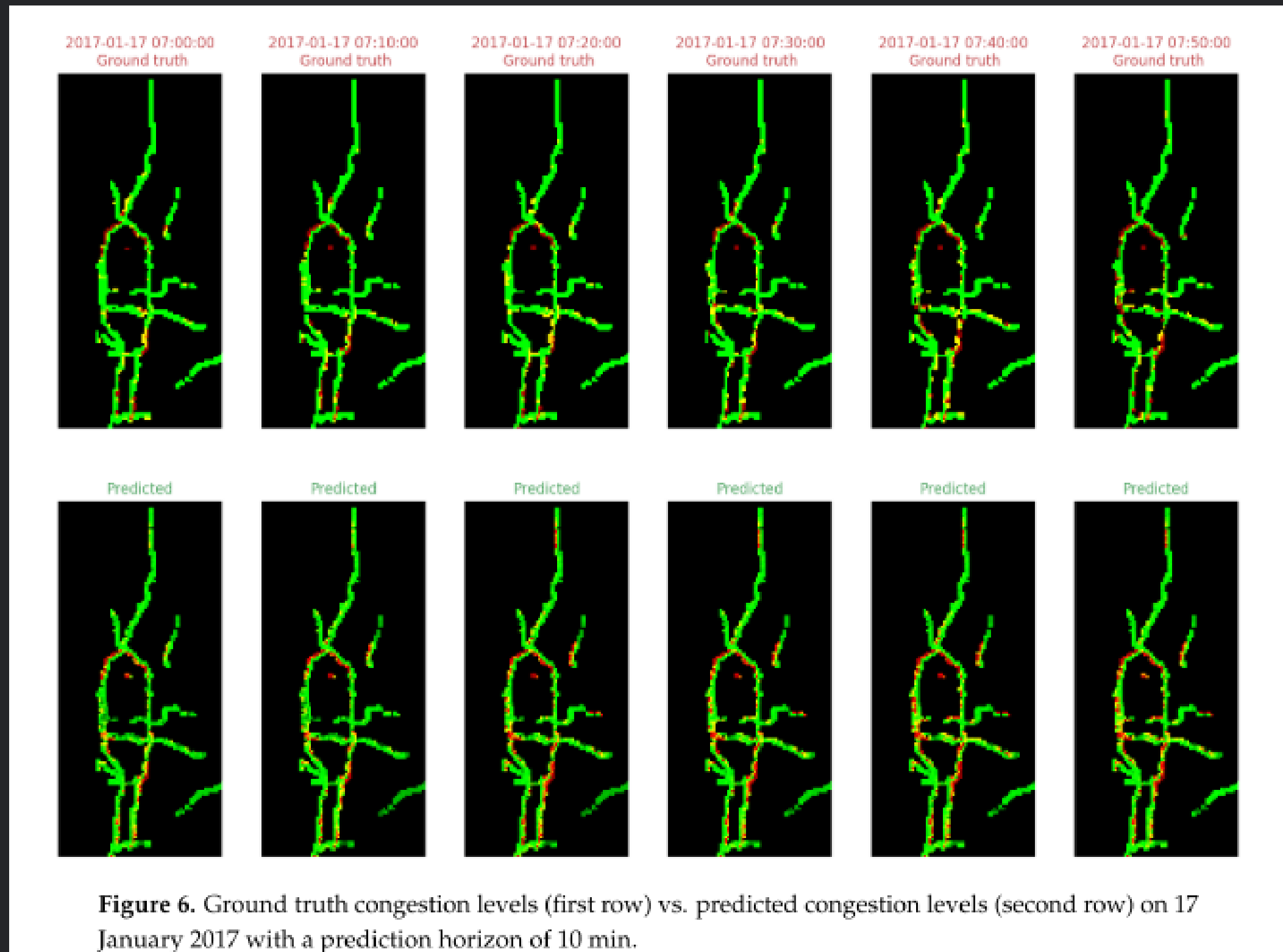
Resultados - Eficiencia

Table 6. Computing resources for training with prediction horizons of 10, 30, and 60 min.

10 min				
metric description		SRCN	ConvLSTM	DCPN
total number of epochs to converge		876	719	823
total training time (s)		30,646.517	70,125.471	21,450.032
30 min				
metric description		SRCN	ConvLSTM	DCPN
total number of epochs to converge		757	631	845
total training time (s)		26,572.629	61,677.397	22,235.832
60 min				
metric description		SRCN	ConvLSTM	DCPN
total number of epochs to converge		769	690	795
total training time (s)		27,585.755	66,646.381	20,299.434

Resultados

17 enero 2017 - Horizonte de predicción de 10 minutos



Conclusiones

- Herramienta de predicción de congestión a través de imágenes
 - Accesible

Conclusiones

- Herramienta de predicción de congestión a través de imágenes
 - Accesible
- Construcción de modelo DPCN

Conclusiones

- Herramienta de predicción de congestión a través de imágenes
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Conclusiones

- Herramienta de predicción de congestión a través de imágenes
 - Accesible
- Construcción de modelo DPCN
- DPCN es mas efectivo
- DPCN es mas eficiente

Investigaciones Futuras

- Incluir mas información

Investigaciones Futuras

- Incluir mas información
- Utilizar imágenes de otros sistemas

Investigaciones Futuras

- Incluir mas información
- Utilizar imágenes de otros sistemas
- Cuantificar cuanta información se pierde

Investigaciones Futuras

- Incluir mas información
- Utilizar imágenes de otros sistemas
- Cuantificar cuanta información se pierde
- Mejorar la eficiencia dejando de considerar valores 0

Opiniones Personales

- Valor de la herramienta

Opiniones Personales

- Valor de la herramienta
- Dudas respecto a la bidireccionalidad

Opiniones Personales

- Valor de la herramienta
- Dudas respecto a la bidireccionalidad
- Enfoque en transsporte urbano

Opiniones Personales

- Valor de la herramienta
- Dudas respecto a la bidireccionalidad
- Enfoque en transporte urbano
- Relación con investigación

Deep Autoencoder Neural Networks for Short-Term Traffic Congestion Prediction of Transportation Networks

SEN ZHANG, YONG YAO, JIE HU, YONG ZHAO, SHAOBO LI, JIANJUN HU (2019)

Anexos

Herramientas del estudio

Acercamiento al procesamiento de
imagenes sobre niveles de congestion

Modelo eficiente de predicción de
congestión de la red

Resultados eficientes y efectivos

Resultados

Table 4. Configuration of parameters for DCPN.

Layer	Name	Channels	Shape
0	Inputs	1	(11, 149, 69)
1	Flattern	1	113,091
2	Dense (ReLU)	1	512
3	Dense (ReLU)	1	384
4	Dense (ReLU)	1	256
5	Dense (ReLU)	1	128
6	Dense (ReLU)	1	128
7	Dense (ReLU)	1	256
8	Dense (ReLU)	1	384
9	Dense (ReLU)	1	512
10	Dense (Sigmoid)	1	149×69
11	Dropout (0.1)	—	—
12	Dense (Sigmoid)	1	149×69
13	Reshape	1	(149, 69)

Pasos realizados

- Limpieza de imágenes, a través del procesamiento de imágenes
- Asignación de números por pixel usando HSL

