DE LA RECHERCHE À L'INDUSTRIE

Synthetic Data And Deep Neural Networks For Atmospheric Dispersion Modelling In Urban Areas

HARMO 20

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Overview

1.1 Scope of the Study

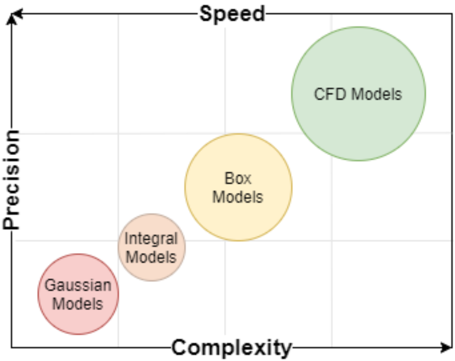
- Unexpected pollution emissions in urban areas : accidental (*e.g.* chemical accidents) or malicious (*e.g.* hostile fire)

FIGURE – Philadelphia Refinery Explosion (Forbes, 2019)

- Emergency crisis intervention from the authorities to protect the population and the environment

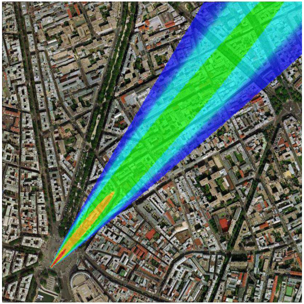
- Need for **fast** and **accurate** pollution models to estimate exposure risks and provide recommendations to decision makers

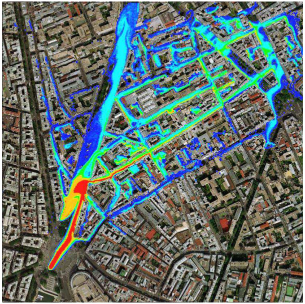
1.2 Air Pollution Models



- Several families of models
- Trade-off between precision and complexity

1.3 Pollution in urban areas



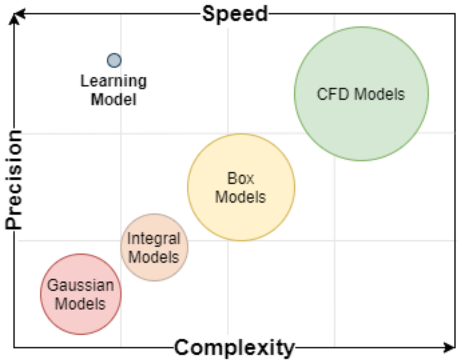


Dispersion predicted with Gaussian (left) and CFD (right) models

(P. Armand, C. Duchenne, and L. Patryl, ITM 2015, France)

- Large model sensitivity in urban areas
- CFD-level accuracy is required for risk assessment

1.3 Contribution



- Feasibility of a transport and dispersion learning model that is :
  - Fast
  - Precise
  - Usable for any urban area

2.1 Machine Learning

"A computer program is said to learn from experience *E* with respect to some class of tasks *T* and performance measure *P*, if its performance at tasks in *T*, as measured by *P*, improves with experience *E*" (Tom Mitchell, 1997)

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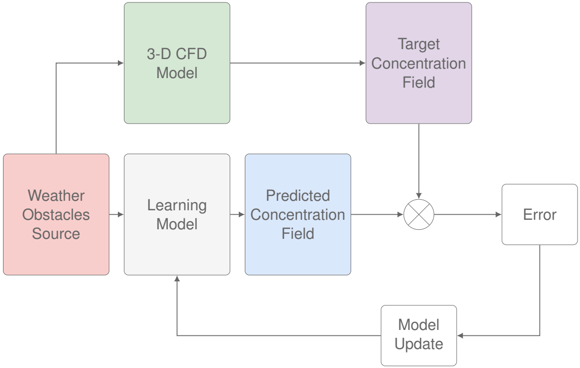
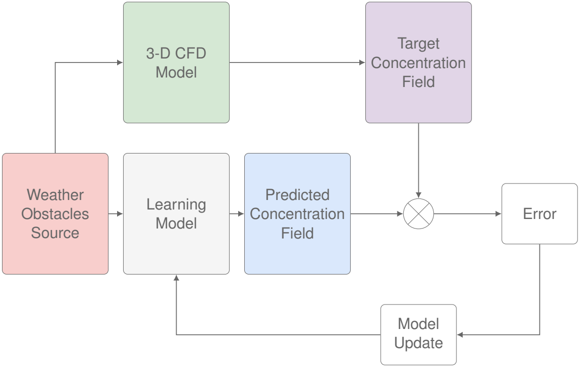
- The task T : how the machine should process the inputs
  - predict the concentration field subsequent to an accidental release
- The performance measure P : quatitative performance at accomplishing the task T
  - mean squarred error between predicted and target concentration values
- The experience E : how the algorithm experiences the data it learns from
  - learning useful transport and dispersion properties from a database of various concentration fields

2.1 The Learning Process (1/2)



- Model inputs : weather, obstacle map, emission source
- Learning model : parametric function of the inputs
- Predicted model outputs : time-integrated concentration field
- Target outputs : ground truth time-integrated concentration field

2.1 The Learning Process (2/2)



- Learning : iterative model update to minimize the prediction error
- Generalization : learned model must perform well on new, previously unseen inputs

2.2 Synthetic Data (1/2)

- Deep learning algorithms requires a large quantity of data
  - Real data from real size or small-scall experiments
    - ☺ High accuracy
    - ☹ Slow and expensive
  - Synthetic data from computer simulations
    - ☻ Model-dependent accuracy
    - ☺ Cheap, relatively fast, flexible

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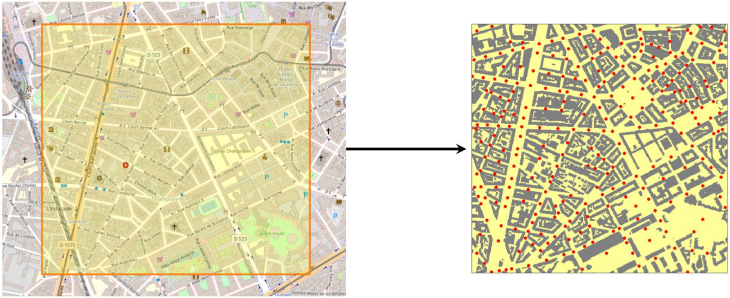
- Synthetic data generated by Parallel Micro-SWIFT-SPRAY (PMSS)
  - 3-D atmospheric transport and dispersion simulator
  - Lagrangian particle dispersion model
  - High time and space resolution
  - Accounts for the presence of obstacles

2.2 Synthetic Data (2/2)

- Training Dataset : city of Grenoble (France)
  - Approx. 15000 PMSS simulations
  - 500 × 500 grid of 2 m space resolution
  - 274 different hypothetical emissions sources
  - 54 different stationary weather conditions



2.3 Learning Model Architecture

- No Free Lunch Theorem : there is no single best learning model suited for all problems
- Problem-related criteria
  - Pre/post-processing : scaling, centering, vectorization
  - Multilayer perceptron : integrated concentration regression
  - Encoder/decoder blocks : (space) dimension reduction

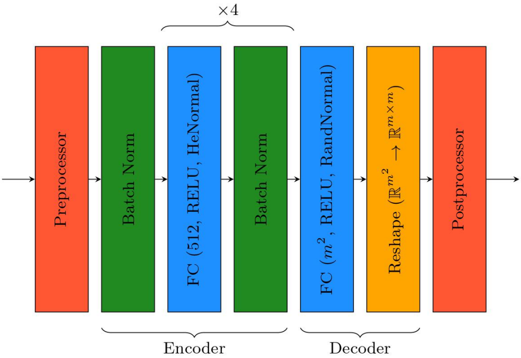
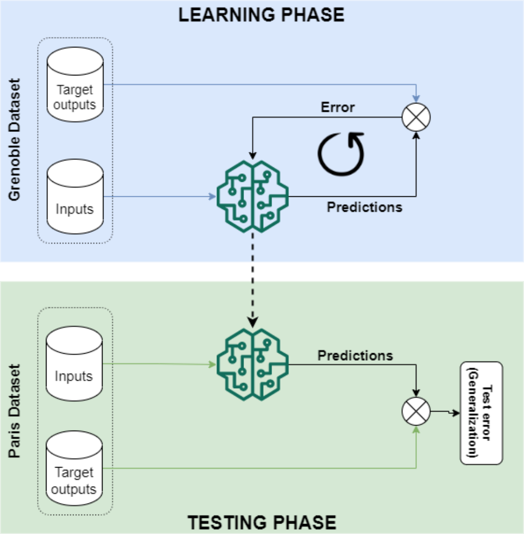


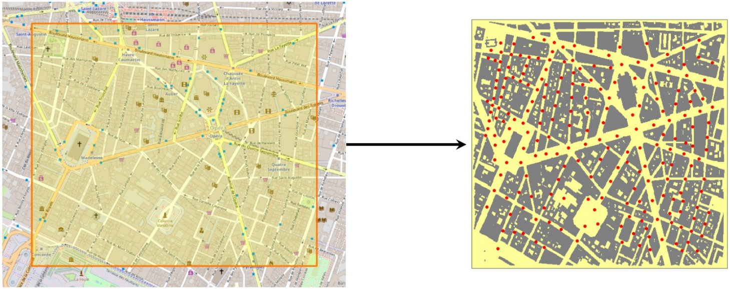
FIGURE – Learning Model Architecture

3.1 Generalization Test



3.1 Test Dataset

- Test Dataset : city of Paris (France)
  - Approx. 12000 PMSS simulations
  - 600 $\times$ 500 grid of 2 m space resolution
  - 222 different hypothetical emissions sources
  - 54 different stationary weather conditions



3.2 Learning Performance

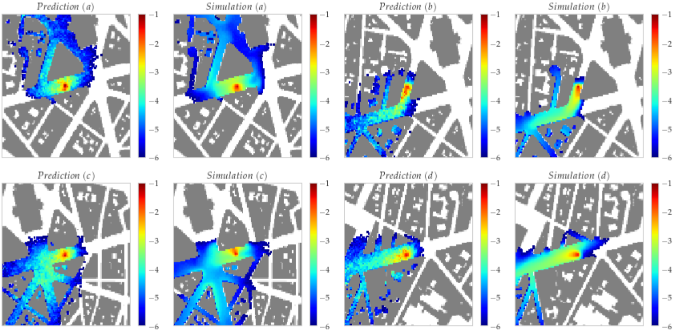


FIGURE – Predictions *vs.* Ground Truth (PMSS simulations) : integrated concentration fields (over 2 hours) in Paris (log scale)

- Average mean squared error : 0.96
  - Accurate dispersion modelling in street intersections
- Fast execution time $\approx$ 0.75 ms per prediction

Conclusions

- Need for fast and accurate models of accidental/malicious air pollution in urban areas
- First learning model of air transport and dispersion usable in any urban area
- The trained model is precise and enables fast predictions
- Next step : joint prediction of horizontal and vertical pollution distributions

Thanks for your attention

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