

Applications of quantum computing and machine learning in transport

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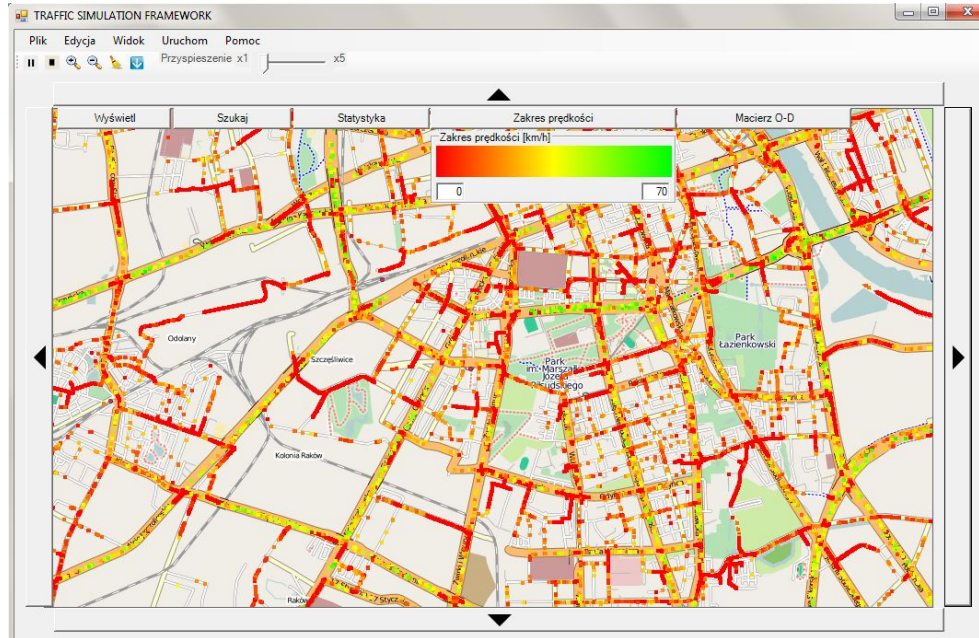
Machine Learning meets Quantum Computation

(Some) applications of machine learning in transport

- Predicting traffic (travel times, flows)
 - Short-term (e.g., 10-15 minutes ahead)
 - Long-term (e.g., after a few hours, next day)
 - Data: traffic counts / flows, nr of passengers (public transport), FCD (floating car data)
 - Typical/regular cases
 - Atypical cases (car accidents, roadworks, mass events)
 - In the past: ARIMA, random forests, SVMs
 - Modern methods: CNN, RNN (LSTM), XGBoost
 - (Cooperation with CE-Traffic company within H2020 “MELODIC” project <http://melodic.cloud>)
- Prediction “what-if”
 - **What** will happen **if** we change something, e.g., traffic signal settings, road network infrastructure

Traffic Simulation Framework

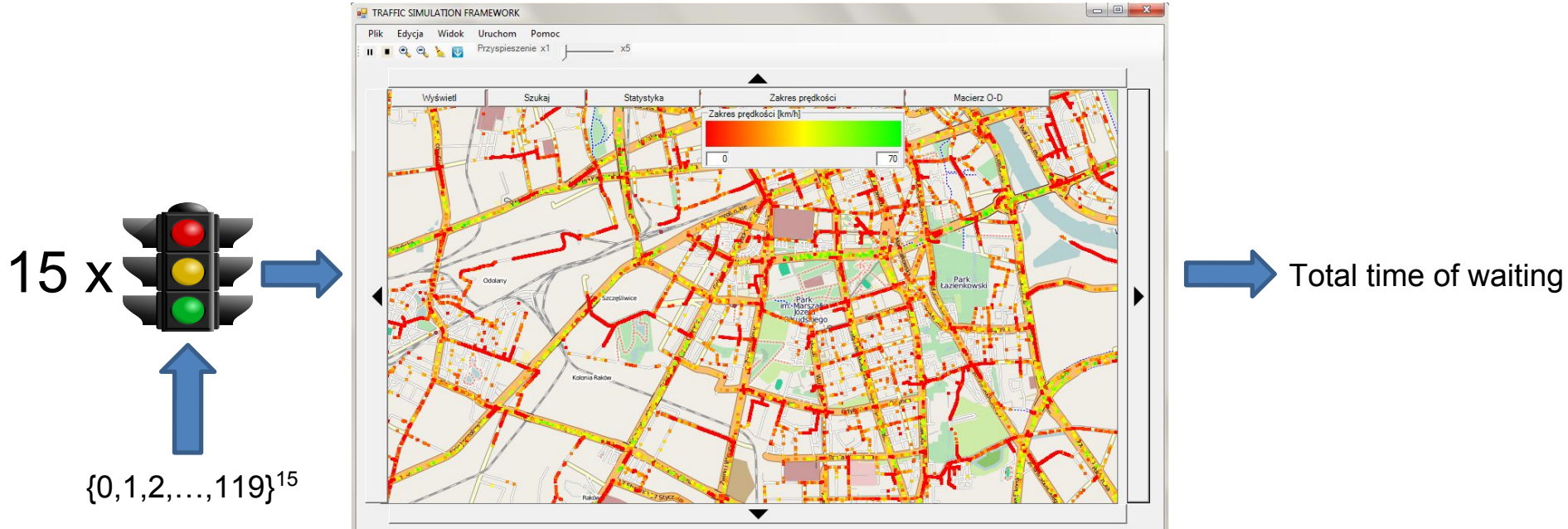
Nowadays, planning road infrastructure is usually done using traffic simulations which investigate many different settings.



But sometimes we have to test large number of settings ...

Traffic Simulation Framework

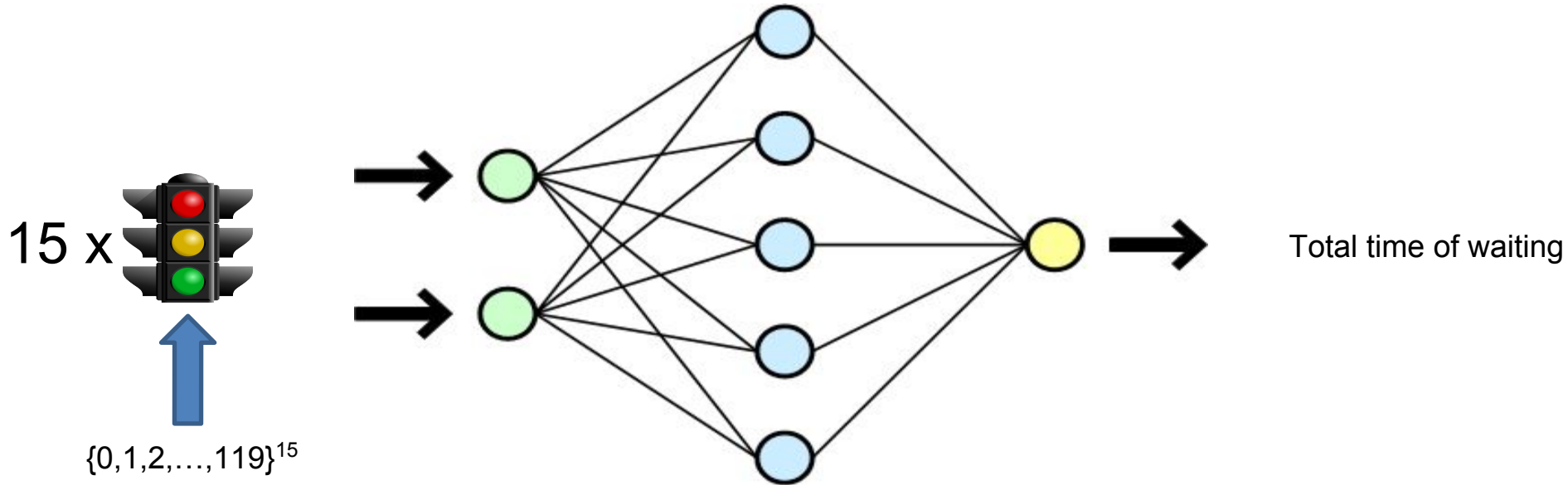
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TensorTraffic

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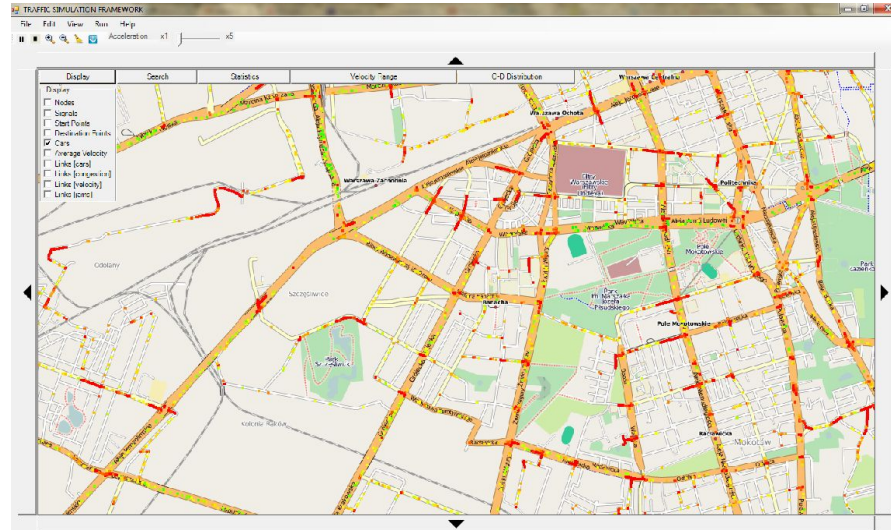


But sometimes we have to test large number of settings ...

TensorTraffic

Using Traffic Simulation Framework we generated set composed of 117033 elements, divided it into training set (81920 elements), validation set (20479 elements) and test set (14634 elements).

Each run simulated 10 minutes of traffic with 42 000 cars on a realistic map of Warsaw (OSM).



TSF implements a microscopic simulation model (extension of the Na-Sch model to the case of arbitrary network)

TensorTraffic



- We developed a **TensorTraffic** tool for approximating outcomes of traffic simulations using NN and predicting what may happen if we change traffic signal settings (“AI with imagination”)
- We tested many architectures of neural networks (NN) and values of NN hyperparameters (learning rate, dropout etc)
- We found out, that, indeed, **outcomes of traffic simulation can be approximated using NN** with a good accuracy (best average error on a validation set: ~1.18%, maximal error: ~6.8%)
- And in the investigated case we don't even need very large / deep neural networks
- (Recently we even improved these results using XGBoost, LightGBM)

TensorTraffic

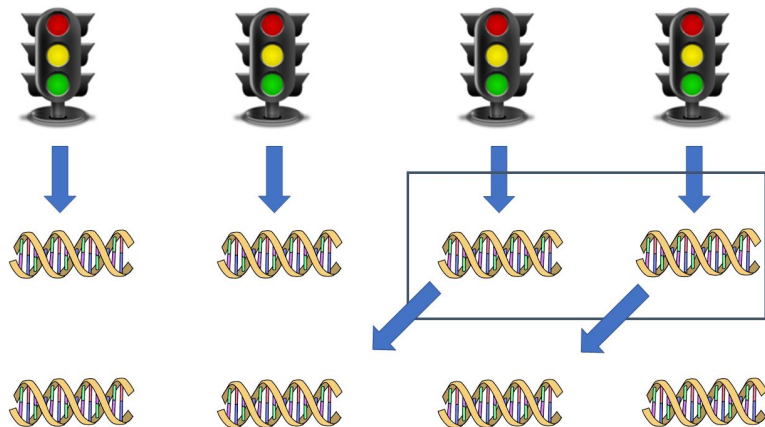


Settings used in experiments:

- Inputs to NN: 15-element vector of signal settings (offsets on 15 crossroads, each offset is from the set $\{0, 1, 2, \dots, 119\}$)
- Outputs of NN: approximated total waiting time of all vehicles in a given area (Stara Ochota)
- Each NN was a feed forward fully connected NN with ReLU activation function
- Training set size: 81920, 30720, 10240
- Configurations of hidden layers in neural networks: [100, 100, 100], [100, 200, 100], [200, 300, 200], [300, 400, 300], [100, 150, 200, 150, 100], [50, 100, 200, 300, 200, 100, 50]
- Values of a learning rate parameter: 0.1, 0.01, 0.001, 0.0001
- Dropout probability (randomly removing some units to prevent overfitting): 0.05, 0.1, 0.15, 0.2

TensorTraffic

Application: optimizing transport, AI-based (and simulation-based) real-time traffic management (optimizing traffic signal settings)



Genetic algorithm:

Fitness function: the total waiting time

Selection: tournament

Crossover: uniform

Mutation: $p=0.05$



Even after 15 iterations we can find settings better by
> 10% than best setting in the initial (random) population

Traffic Optimization

Other considered optimization algorithms:

- Gradient optimization
- Simulated annealing
- Metropolis-Hastings
- Ant colony optimization
- Particle swarm optimization
- ...

Traffic / transport optimization problems:

- Finding optimal traffic signal settings
- Finding optimal locations and capacities of parkings
- Finding optimal locations of charging stations for electric vehicles
- Finding optimal road network infrastructure
- ...

(Also applications in other domains)

The future may be even better

Including connected and autonomous vehicles (CAVs) to find optimal algorithms of drive and traffic management (optimizing traffic safety and efficiency in a large scale)

I am representing Poland in the
Management Committee of the COST Action:

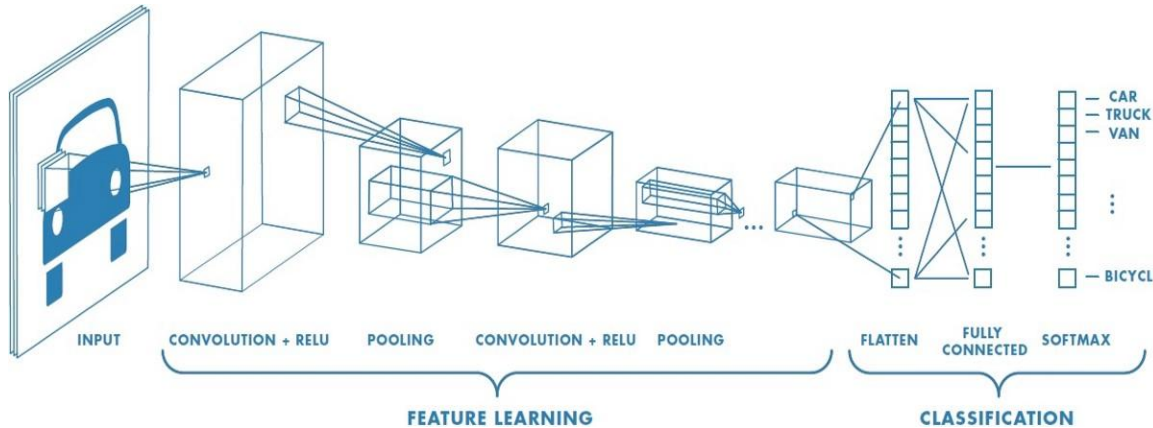
**“Wider Impacts and Scenario Evaluation
of Autonomous and Connected Transport”**



Source: <http://time.com/4129247/google-self-driving-cars-patent>

The future may be even better

Recognizing objects on roads using computer vision (convolutional neural networks)



Source: <http://time.com/4129247/google-self-driving-cars-patent>

An interesting research question: how to assess a risk of collision (needed by car insurance market) ?

The future may be even better

AI on quantum computers?

Volkswagen Uses Quantum Computing to Fight Beijing Traffic

Volkswagen teamed with D-Wave Systems to run a traffic-flow algorithm on a quantum computer, with encouraging results.

BY STEPHEN EDELSTEIN MARCH 30, 2017

Volkswagen and Google to bring quantum computing benefits to cars

Posted Nov 8, 2017 by Darrell Etherington (@etherington)

Optimizing routes of fleets of taxis in Beijing

“Traffic Flow Optimization Using a Quantum Annealer”

Florian Neukart, Gabriele Compostella, Christian Seidel, David von Dollen, Sheir Yarkoni, Bob Parney
(Volkswagen + D-Wave)

<https://www.frontiersin.org/articles/10.3389/fict.2017.00029/full>

Quantum annealing - suitable for solving complex combinatorial optimization problems

- We build a road network and have routes from real GPS data (T-Drive, taxis in Beijing))
- For each car we add 2 possible routes between source and destination (cars may share road segments)
- Travel time is proportional to the function (square) of a number of cars on a route (simplification)
- We want to minimize the total travel time

Optimizing routes of fleets of taxis in Beijing

- q_{ij} - 0 or 1 (car i takes route j)

$$\begin{aligned} 0 &= \left(\sum_{j \in \{1,2,3\}} q_{ij} - 1 \right)^2 \\ &= -q_{i1} - q_{i2} - q_{i3} + 2q_{i1}q_{i2} + 2q_{i2}q_{i3} + 2q_{i1}q_{i3} + 1 \end{aligned}$$

- B_s - set of q_{ij} associated with routes that share street segment s

$$\text{cost}(s) = \left(\sum_{q_{ij} \in B_s} q_{ij} \right)^2$$

$$\text{Obj} = \sum_{s \in S} \text{cost}(s) + \lambda \sum_i \left(\sum_j q_{ij} - 1 \right)^2$$

Optimizing routes of fleets of taxis in Beijing

$$\text{Obj} = \sum_{s \in S} \text{cost}(s) + \lambda \sum_i \left(\sum_j q_{ij} - 1 \right)^2$$

$$\text{Obj}(x, Q) = x^T \cdot Q \cdot x$$

QUBO - Quadratic unconstrained binary optimization

Given the matrix Q , finding binary variable assignments to minimize the objective function is equivalent to minimizing an Ising model (model of ferromagnetism), which is NP-hard.

It can be solved using quantum annealing on D-Wave (in this case: D-Wave 2X QPU)

Optimizing routes of fleets of taxis in Beijing

“**Quantum annealing** - starts from a quantum-mechanical superposition of all possible states (candidate states) with equal weights. Then the system evolves following the time-dependent **Schrödinger equation**, a natural quantum-mechanical evolution of physical systems. The amplitudes of all candidate states keep changing, realizing a quantum parallelism, according to the time-dependent strength of the transverse field, which causes quantum tunneling between states. If the rate of change of the transverse-field is slow enough, the system stays close to the ground state of the instantaneous Hamiltonian, i.e., **adiabatic quantum computation**. If the rate of change of the transverse-field is accelerated, the system may leave the ground state temporarily but produce a higher likelihood of concluding in the ground state of the final problem Hamiltonian, i.e., diabatic quantum computation. The transverse field is finally switched off, and the system is expected to have reached the ground state of the classical **Ising model** that corresponds to the solution to the original optimization problem. An experimental demonstration of the success of quantum annealing for random magnets was reported immediately after the initial theoretical proposal.”

(https://en.wikipedia.org/wiki/Quantum_annealing , 26.04.2018)

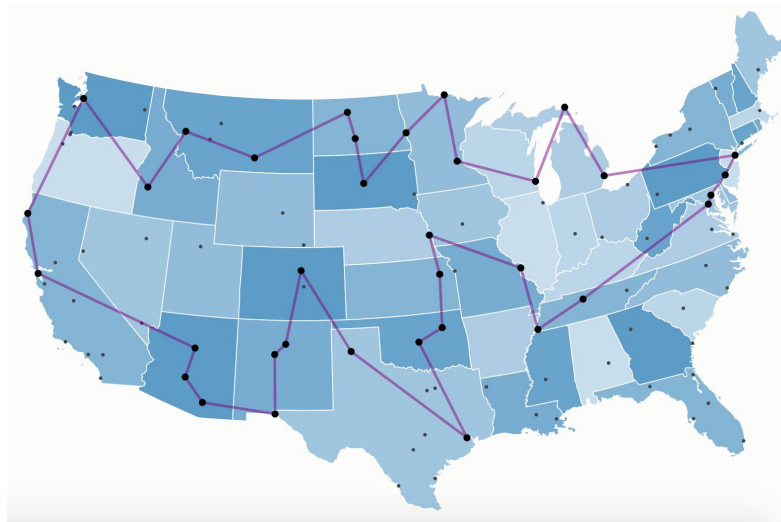
Simple: finding minimal energy state for a given problem (encoded as entanglement of qubits).

Nice explanation from D-Wave:

https://www.youtube.com/watch?v=UV_RICAc5Zs

Improving logistics

- Solving Travelling Salesman Problem (NP-hard)
- Quantum Approximate Optimization Algorithm (QAOA, <https://arxiv.org/pdf/1411.4028.pdf>)
- There are already logistic companies interested in such solutions!



Source: <http://examples.gurobi.com/traveling-salesman-problem>

Quantum AI

Training machine learning algorithms using QC (usually with support of classical computers):

- Quantum sampling, Quantum Monte Carlo
- Calculating average (expected) gradients
- Manipulating matrices
- Solving optimization problems (which often occur in AI/machine learning)
- Distance matrix (k-Means), Quantum kNN
- Quantum SVM
- Quantum Boltzmann Machines
- ...

Great video / interview with scientists from Microsoft Research:

<https://channel9.msdn.com/Shows/Microsoft-Research/Research-in-Focus-Transforming-Machine-Learning-and-Optimization-through-Quantum-Computing>

Quantum mechanics may be responsible for (real) intelligence, consciousness (*quantum brain*).

Thank you!

Questions?

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www: <http://www.mimuw.edu.pl/~pawelg>

I invite you to join TensorCell (my research project) and the “Quantum AI” group:
<https://www.facebook.com/groups/363406960787504>

(more than 370 people already there!)

“Logic can get you from A to B, imagination will take you everywhere” A. Einstein

“The sky is NOT the limit”

