Transfer Learning in Wireless Channel Prediction

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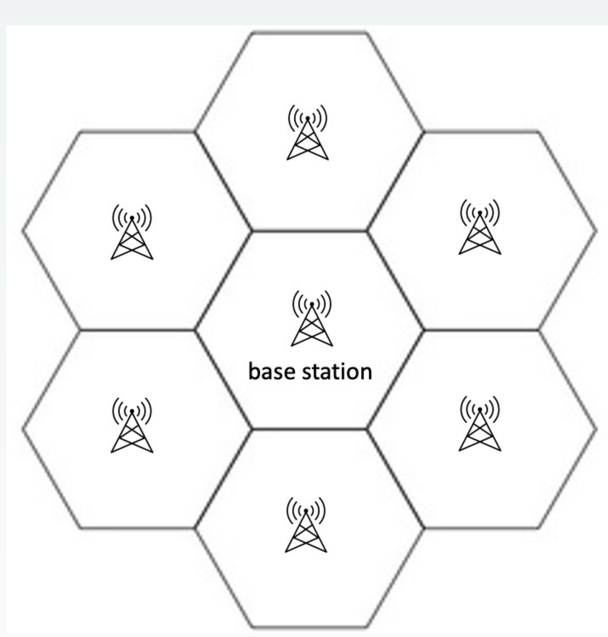
Introduction

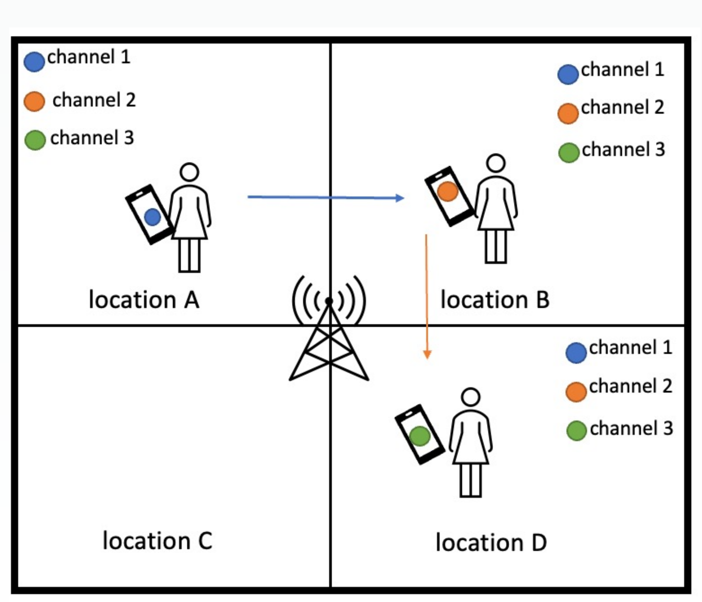
Cellular systems
- Transmit data via radiofrequency (RF) signals
- Provide RF channels for data transmission services
- Four major components
1. Cellular towers and antennas
2. Public switched telephone network (PTSN)
3. Mobile telephone switching office (MTSO)
4. Mobile subscriber units (MSU)

Channel switching
- Switch RF channels based on
1. User location
2. Signal strength
3. Availability

Transfer learning
- Transfers knowledge from one domain to another
- Subfield of machine learning
- Applications
1. Computer vision (CV)
2. Natural language processing (NLP)



Cellular systems.



RF channel switches based on user location.

TAPIA and STARS Celebration
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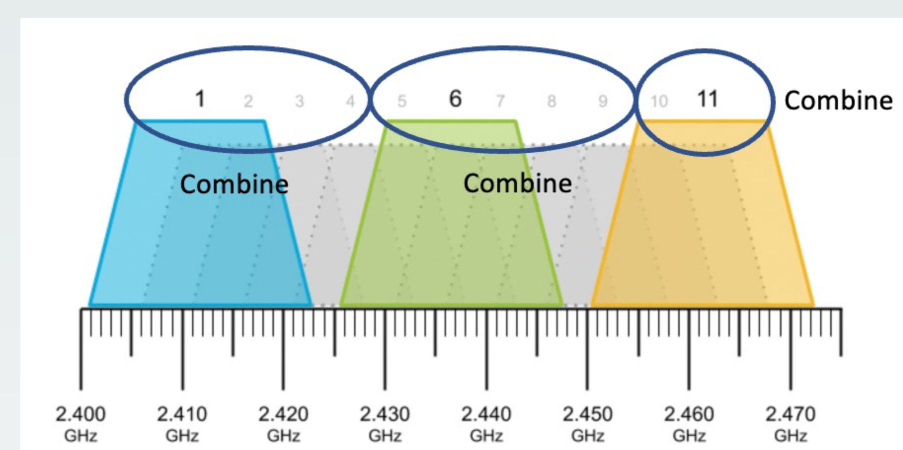
Problem Formulation

RF channel switching is
1. Time-consuming
2. Resource-intensive

Transfer learning is
1. Less time-consuming to train models
2. Less data-dependent to train models

Goal: Minimize channel switching

RF channels overlap in 2.4 GHz band
- Combine overlapping channels

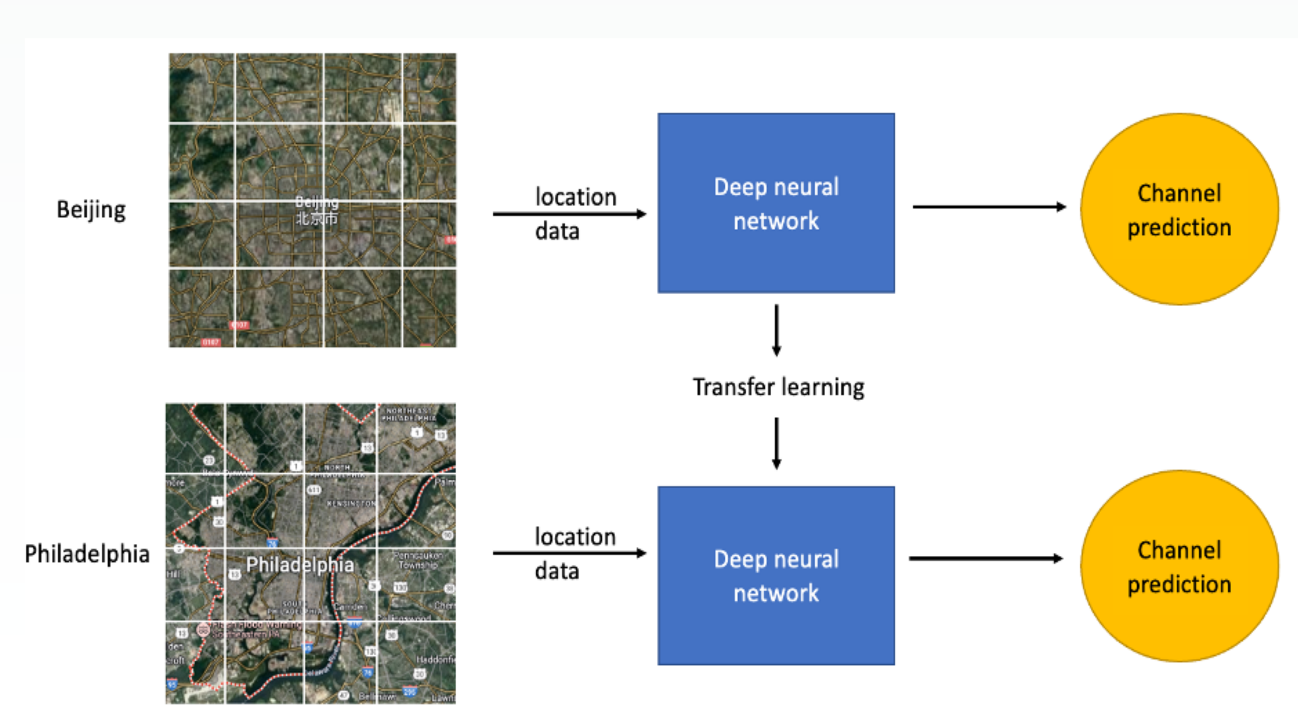


RF channel are combined in dataset.

Instance-based transfer learning

Homogeneous transfer learning
- Source and target domains have similar tasks

Instance-based transfer learning
- Corrects marginal and distribution differences
- Assign weights to the loss function of source domain
- Target domain uses the assigned weights



The knowledge gained from Beijing (City A) can transfer to Philadelphia (City B).

Weighting strategy
- $\mathbb{E}_{(x,y)\sim P^T}[\mathcal{L}(x,y;f)] = \mathbb{E}_{(x,y)\sim P^S}\left[\frac{(P^T(x,y))}{(P^S(x,y))}\mathcal{L}(x,y;f)\right]$
- $E_{(x,y)}$ is the expected risk
- x is the pattern in the
- domain
- y is the label in the domain
- $L(x,y;f)$ is the loss function that depends on the parameter f
- $P^T(x)$ is source domain, $P^S(x)$ is target
- $\frac{(P^T(x,y))}{(P^S(x,y))}$: Instances are drawn from source, and generalized to target
- Generalized instances are now the weighting parameters -> β (x, y)

- Estimate the weighting parameter
- $\min_f \frac{1}{n^s}\sum_{i=1}^{n^s}\beta_i\mathcal{L}(f(x_i^s),y_i^s)+\Omega(f)$
- β_i is the weighting parameter
- n is the number of instances
- Ω(f) is the regularizer of the re-weighted risk

Proposed Simulation Techniques

Two cities examined:
- City A (Beijing) and City B (Philadelphia)
- City A -----transfer knowledge---→ City B

Basic model for simulations
- 7-layer DNN for model training
- Latitude + Longitude ~ Channel
- Predict occupied channels of location

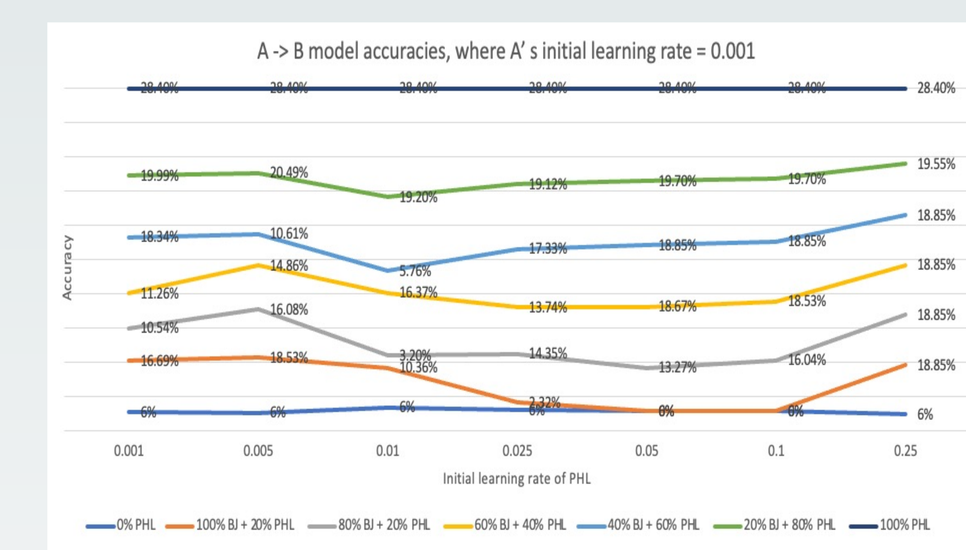
Baseline and Upper bound
- Baseline: averaging 100 accuracy of City A –transfer → City B results
- Upper bound: result of training City B model

Varying training data ratio
1. Train certain % of A data
2. Use the same model, train certain % of B data
3. Different combinations of % A and B data

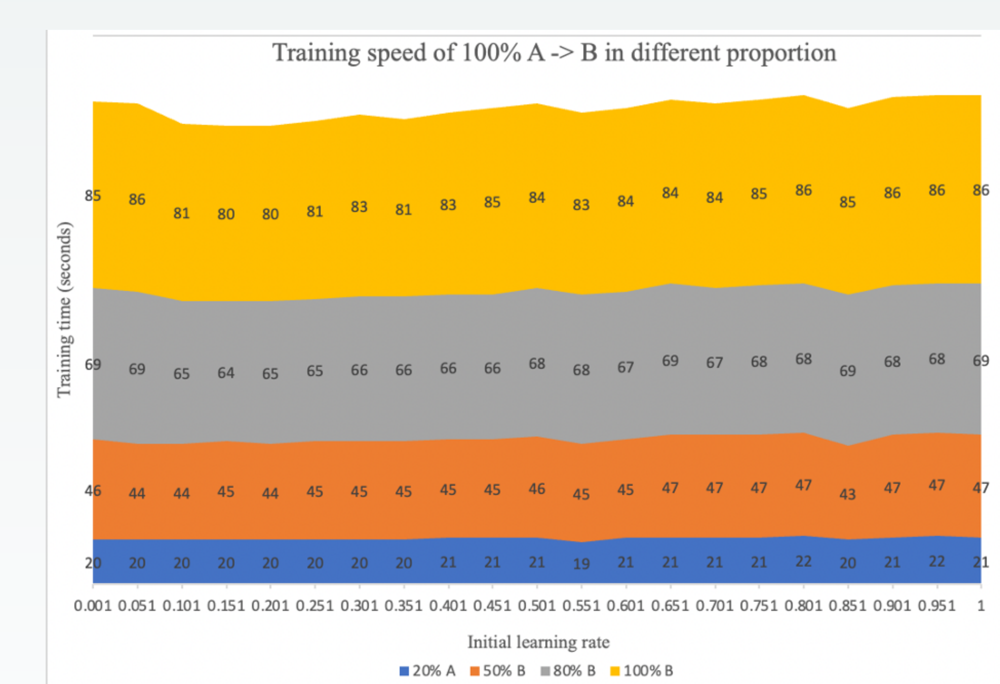
Fine-tune initial learning rates
1. Assign a set of learning rate (LR) for City A
2. For each LR of City A, a set of LR assigns to City B
3. For each pair of LR (LR_A, LR_B), train model with different combinations of Cities A and B data

Training time vs. accuracy
1. Assign a set of LR for training
2. Cities A and B use the same LR
3. Train City A --> B in different %
4. Record training time and accuracy

Evaluation



- As % B increases, accuracy increases.



- Training speed of A → B.
- Uses less training time while maintaining some level of accuracy.

Conclusion

- Transfer learning is feasible in predicting the used channels in each location
  - Propose simulation techniques
  - Fine tune DNN model and adjust data ratio to generate test results
  - Experiments verify the performance
  - Useful when time and data are scarce