# EXPLORING TRANSFERABILITY MEASURES AND DOMAIN SELECTION IN CROSS-DOMAIN SLOT FILLING

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**Code Repository:**
https://github.com/lxcnju/CDSF-Transferability

Learning And Mining from DatA
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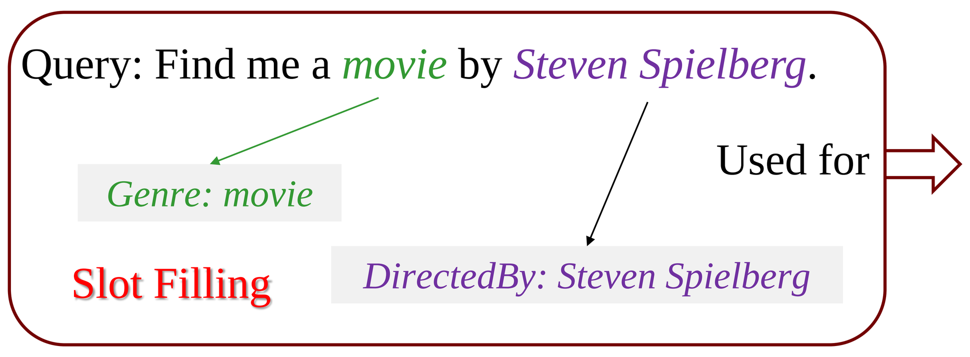
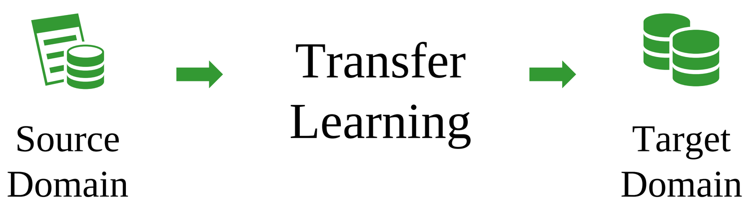
## Background

**Definition of slot filling:**

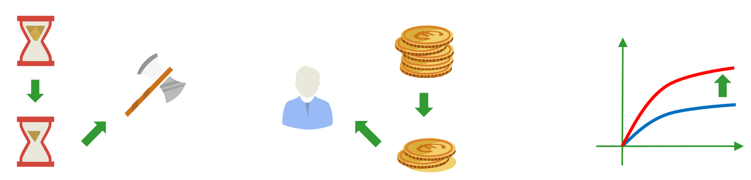
- Slot filling aims to identify the contiguous spans of specific slots in an utterance.
- Slot filling usually co-occurs with intent detection [1].
- Slot filling is fundamental to natural language understanding.




**Transfer Learning:**
Transfer learning utilizes the knowledge obtained from the source domain to facilitate the learning process of the target domain.



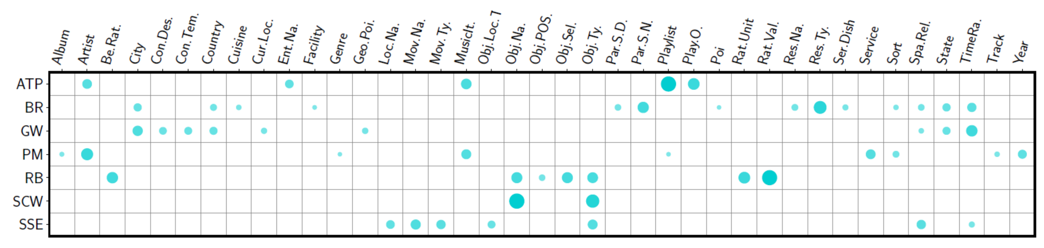

Using transfer learning can save training time, decrease labelling cost and promote model performance.



**Cross Domain Slot Filling:**
In real-world applications, the labeling costs of utterances may be expensive, and transfer learning techniques have been developed to ease this problem.
However, cross-domain slot filling could significantly suffer from *negative transfer* due to *non-targeted* or *zero-shot* slots.

Slot Types of AddToPlaylist (ATP) (**Source Domain**):
[Artist] [*Entity Name*] [Music Item] [Playlist] [*Playlist Owner*]

Slot Types of PlayMusic (PM) (**Target Domain**):
[*Album*] [Artist] [*Genre*] [Music Item] [Playlist] [*Service*] [*Sort*] [*Track*] [*Year*]

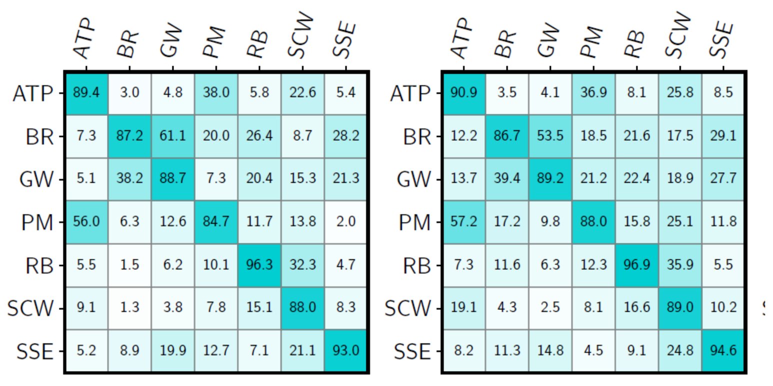



*Slot Distribution in Snips Benchmark*

## Domain Transferability Measures in CDSF

**DT-CDP:**
Measuring Domain Transferability (DT) via Cross-Domain Performance (CDP)

$$\mathrm{Trf}(S \to T) = F1_{x,y \sim \mathcal{T}_{xy}}(y, x; \theta_S)$$

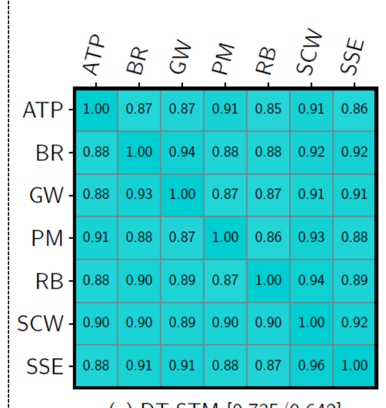


(a) DT-CDP (Coarse) [0.811 w.(b)] (b) DT-CDP (Coach) [0.811 w.(a)]

Metric: Slot F1 Scores
The *Spearman* correlation between Coarse and Coach CDPs is 0.811.

**DT-STM:**
Measuring Domain Transferability (DT) via Slot Transferability Measure (STM)

Calculate STM:
Step 1: collect slot value/context representations $\Omega_v$, and $\Omega_c$.
Step 2: calculate value/context MMD
$d_v = \mathrm{MMD}(\Omega_{vs}, \Omega_{vt})$ $d_c = \mathrm{MMD}(\Omega_{cs}, \Omega_{ct})$
Step 3: transferability among slots
$\mathrm{STM}(s,t) = 1.0 - \tanh\left(\frac{(1+\beta^2)d_v d_c}{\beta^2 d_v + d_c}\right)$
Step 4: transferability among domains
$\mathrm{Trf}(S,T) = \max_{C \geq 0} \sum_{i,j} C_{ij} \mathrm{STM}(i,j)$,
$s.t. \sum_{j=1}^{n} C_{ij} = \frac{1}{m}, \sum_{i=1}^{m} C_{ij} = \frac{1}{n}$.

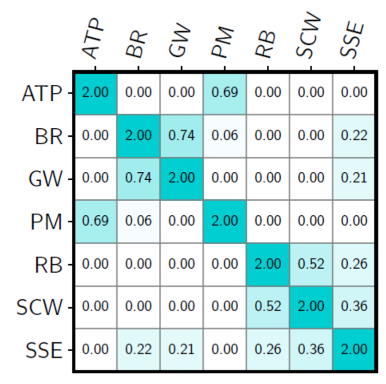


(c) DT-STM [0.735/0.642]

The *Spearman* correlation with two types of CDPs is 0.735 and 0.642.

**DT-SDD:**
Measuring Domain Transferability (DT) via Slot Distribution Discrepancy (SDD)

Calculate SDD:
Step 1: obtain source and target slot distribution $P_S$ and $P_T$
$P_{\star,i} = \frac{\#s_i}{\sum_j \#s_j}, \star \in \{S,T\}$
Step 2: calculate SDD
$\mathrm{Trf}(S,T) = 2.0 - |P_S - P_T|_1$



(d) DT-SDD [0.757/0.666]

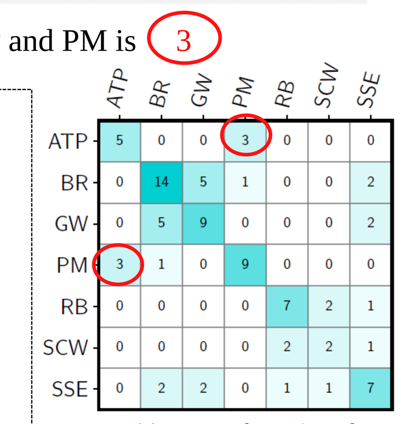
The *Spearman* correlation with two types of CDPs is 0.757 and 0.666.

**DT-SSN:**
Measuring Domain Transferability (DT) via Shared Slot Number (SSN)

Slot Types of AddToPlaylist (ATP) (Source Domain): [Artist] [*Entity Name*] [Music Item] [Playlist] [*Playlist Owner*]
Slot Types of PlayMusic (PM) (Target Domain): [*Album*] [Artist] [*Genre*] [Music Item] [Playlist] [*Service*] [*Sort*] [*Track*] [*Year*]

SSN of ATP and PM is 3

Calculate SSN:
Step 1: obtain source and target types
$C_S = \{s_i\}_{i=1}^{m}$ and $C_T = \{t_j\}_{j=1}^{n}$
Step 2: calculate SSN
$\mathrm{Trf}(S,T) = |C_S \cap C_T|$

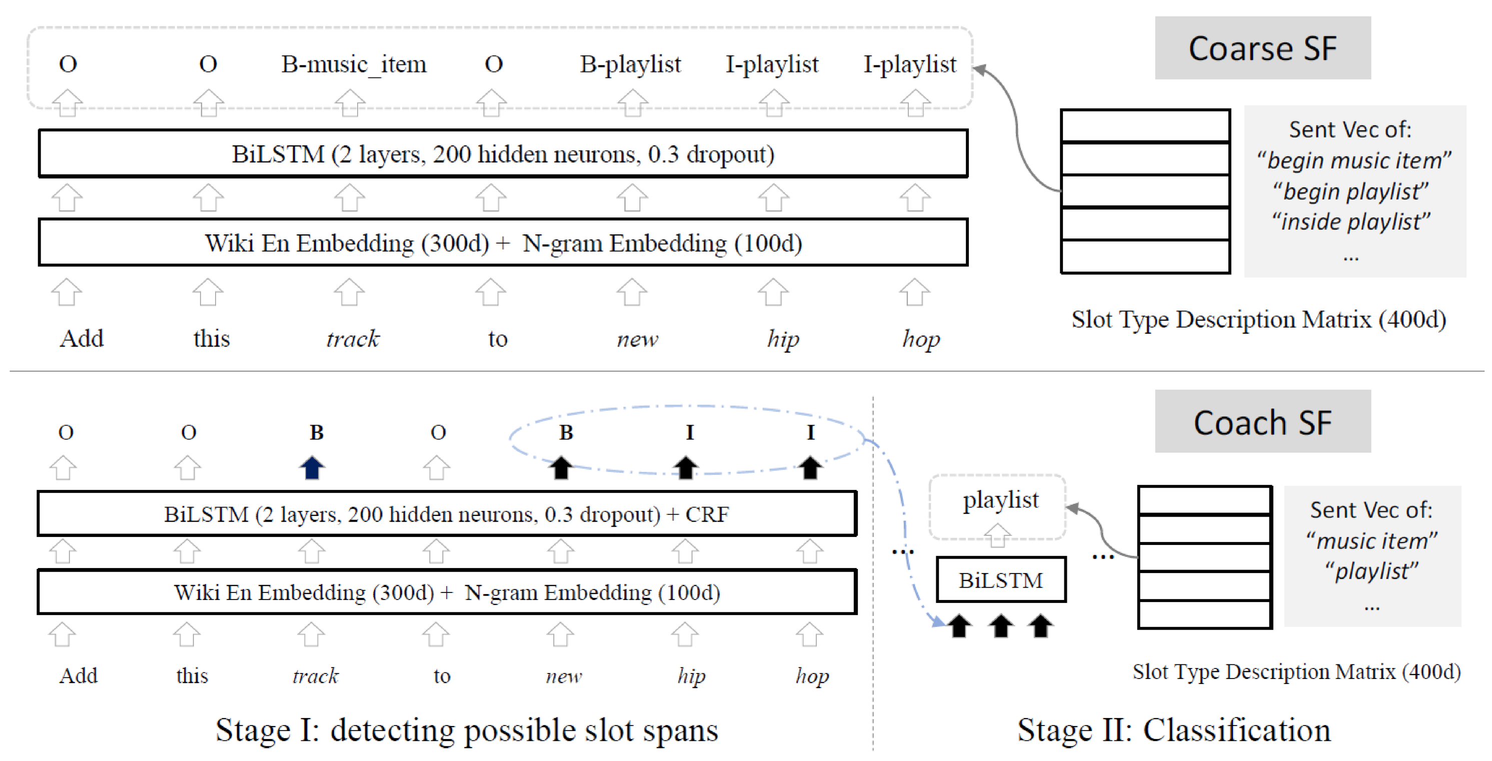


(e) DT-SSN [0.801/0.730]

The *Spearman* correlation with two types of CDPs is 0.801 and 0.730.

## Benefits of DT-SSN

**Slot Filling Architectures:**
Two types of Slot Filling (SF) methods. Coarse SF solves slot filling via end-to-end sequence labeling, while Coach SF decomposes this process into two stages.




**CDSF SOTA Results via Domain Selection:**
**Coach-k**: for a target domain, select top-k source domains via SSN, then train a model on these domains' data and transfer this model to the target domain
**Compared SOTA Methods**: CT, RZT, Coach, Coach-TR, CZSL-A, STM

| | CT [3] | RZT [11] | Coach [4] | Coach-TR [4] | CZSL-A [7] | STM [17] | Coach-1 | Coach-3 |
|---|---|---|---|---|---|---|---|---|
| ATP | 38.82 | 42.77 | 45.23 | 50.90 | 53.89 | 50.54 | **57.22** | 54.81 |
| BR | 27.54 | 30.68 | 33.45 | 34.01 | 34.06 | 32.89 | **39.40** | 38.92 |
| GW | 46.45 | 50.28 | 47.93 | 50.47 | 52.24 | **62.38** | 53.55 | 51.97 |
| PM | 32.86 | 33.12 | 28.89 | 32.01 | 34.59 | 34.45 | 36.95 | **39.27** |
| RB | 14.54 | 16.43 | 25.67 | 22.06 | **31.53** | 25.39 | 16.63 | 18.26 |
| SCW | 39.79 | 44.45 | 43.91 | 46.65 | 50.61 | 52.21 | 35.86 | **53.88** |
| FSE | 13.83 | 12.25 | 25.64 | 25.63 | 30.05 | 26.05 | 29.07 | **31.31** |
| Avg | 30.55 | 32.85 | 35.82 | 37.39 | 40.99 | 40.56 | 38.38 | **41.20** |

Coach-TR and CZSL-A introduces additional techniques to enhance model performances. However, our methods does not introduce any complex training techniques and could still obtain SOTA results.

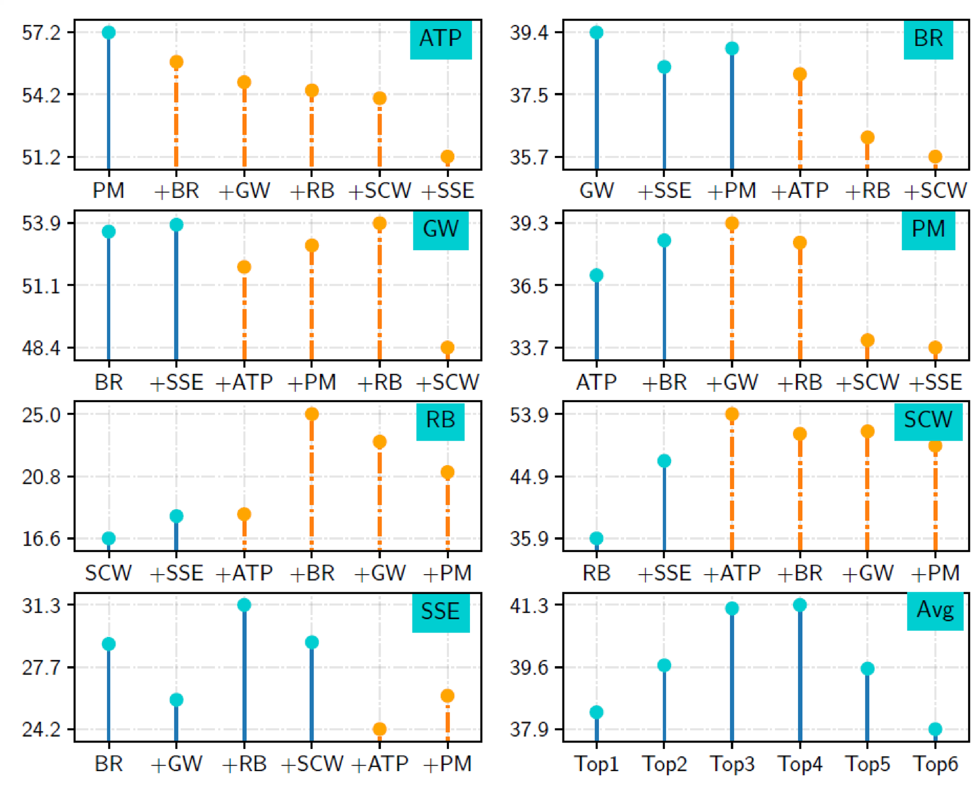
## Benefits of DT-SSN

**Dynamic Transfer:**
Step 1: for a target domain, sort the source domains via SSN

Step 2: train models via sequentially adding source domains, record the transfer performance

**Right Figure**: The dynamic transfer results based on Coach SF. Each plot shows a target domain. The last shows the average results.

The F1 scores continually decrease on most domains when non-overlapped domains (solid yellow bars) are continually added.




## Conclusion

- We explore several domain transferability measures in CDSF.
- Shared Slot Number (SSN) is a frustratingly easy domain transferability measure.
- We clearly show the negative transfer phenomenon in CDSF.
- Based on SSN, we propose to use this estimator to select domains and obtain SOTA results on Snips.