ESR 12

Source domain selection for transfer learning applications

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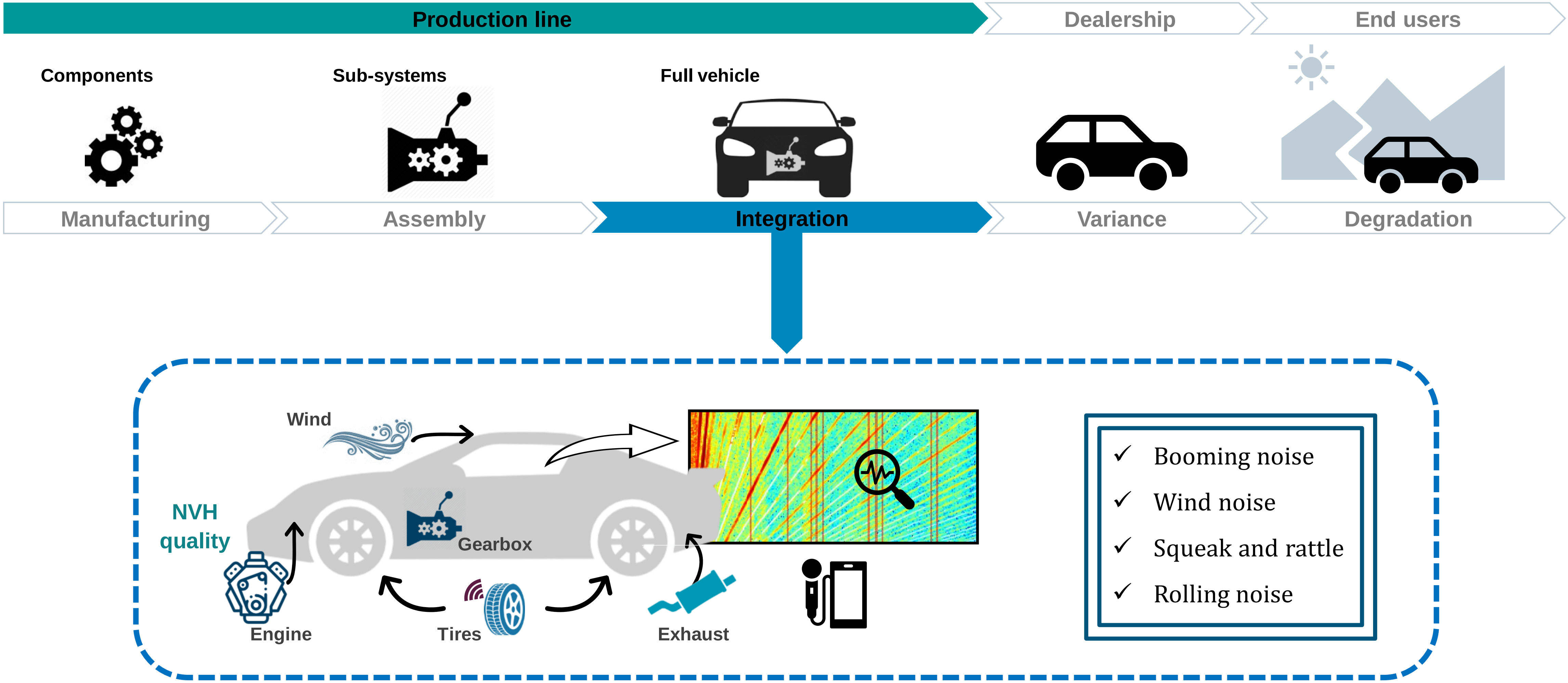
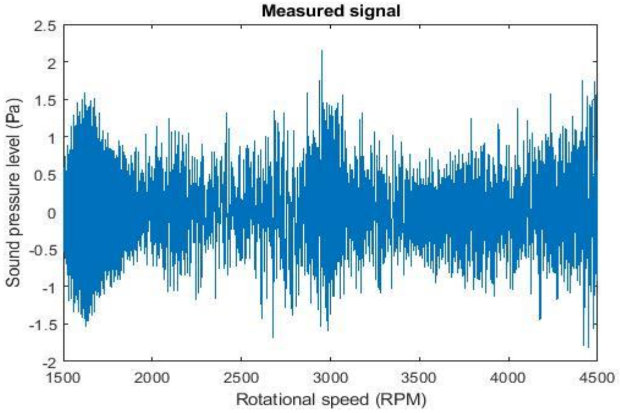
End-of-line testing and monitoring in fleets

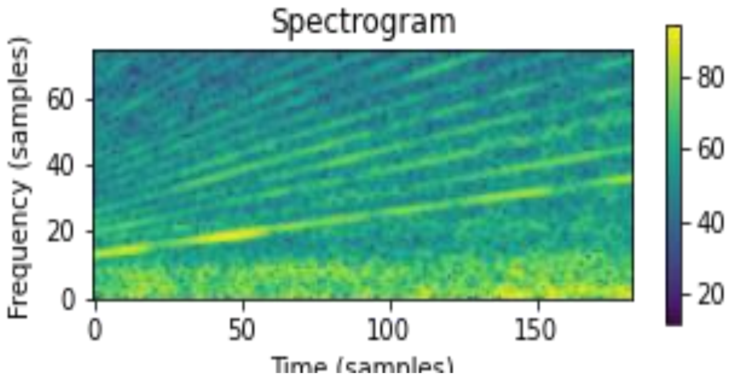


Booming noise

Booming noise is a low frequency structure-borne noise in the interior of a vehicle which causes discomfort to passengers and thus affecting the vehicle sound quality.



Time signal



Spectrogram

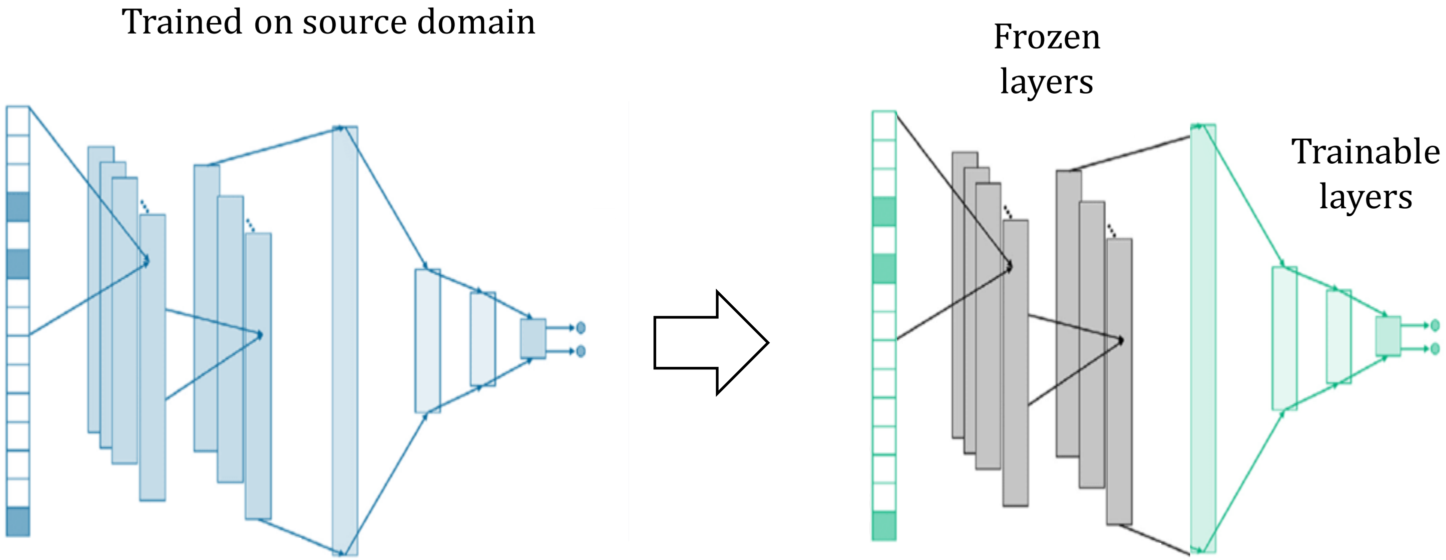
Transfer learning

- **Transfer learning** is the idea of re-using knowledge learned in one situation for another situation
- A transfer is done **from a source** domain and task **to a target** domain and task
- The **domain** consists of the input feature space X and the marginal probability distribution p(X)
- The **task** is the predictive function learned from training data f

Hadrien Bertrand. Hyper-parameter optimization in deep learning and transfer learning : applications to medical imaging.

Fine tuning

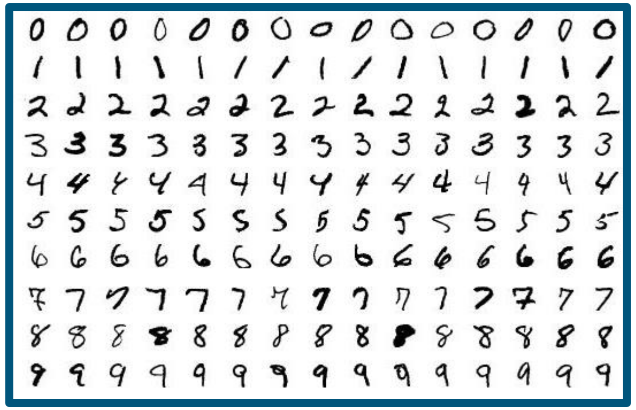
- Applicable when we have a large source dataset and a small target dataset
- Steps:
  1. Select source dataset and task
  2. Train a neural network on the source domain.
  3. The lower layers which capture more generic features are frozen, while the end layers are further trained on the target domain

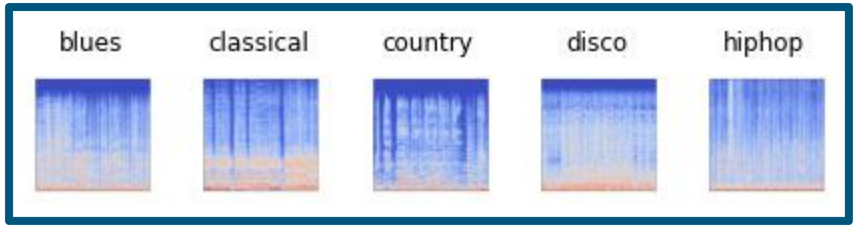


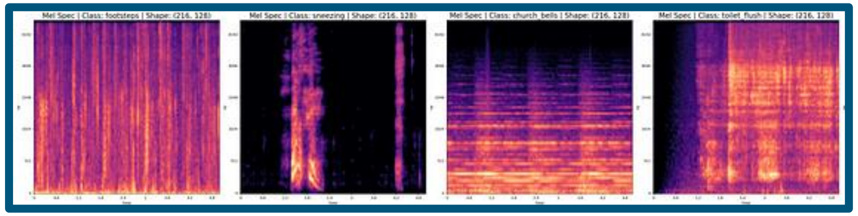
https://livebook.manning.com/book/deep-learning-with-javascript/chapter-5/v-6/114

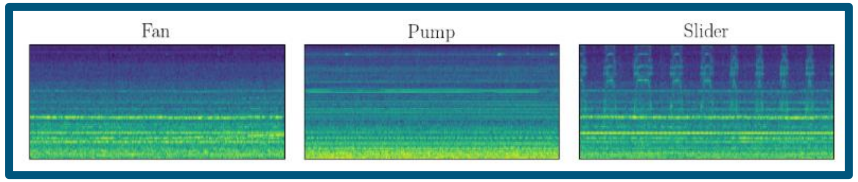
Source domain selection

- Source domain selection is the process of identifying the most suitable source dataset for a given target task in transfer learning.
- For any given task there are multiple candidates for the source domain
- Source domain selection aims to find the ideal source domain prior to training









Source domain selection methods

- **Knowledge based methods**
  - Field experts manually select the most relevant source dataset based on their understanding of the target task and the characteristics of the available datasets.
  - While effective, knowledge-based approaches may be subjective and rely heavily on the expertise of the domain experts.
- **Data-driven methods**
  - These approaches aim to objectively evaluate the compatibility between the source and target domains, allowing for an automated selection process based on empirical evidence rather than expert judgment alone.
  - However, since these approaches rely on quantitative measures of domain similarity and task relevance, they can overlook subtle nuances and context-specific factors that experts might consider.
- **Training driven selection**
  - This method involves training the model to learn weights for each source domain during the training process. In this method, the model dynamically adjusts the weights assigned to different source domains based on their relevance to the target task.
  - While this approach can be effective, it necessitates extensive model training.

Data driven methods

- Euclidean distance
- Manhattan distance
- Maximum Mean Discrepancy (MMD)
- CORrelation ALignment (CORAL)
- Class-wise Network Parameter Averaging (CNPA)

Class-wise Network Parameter Averaging (CNPA)

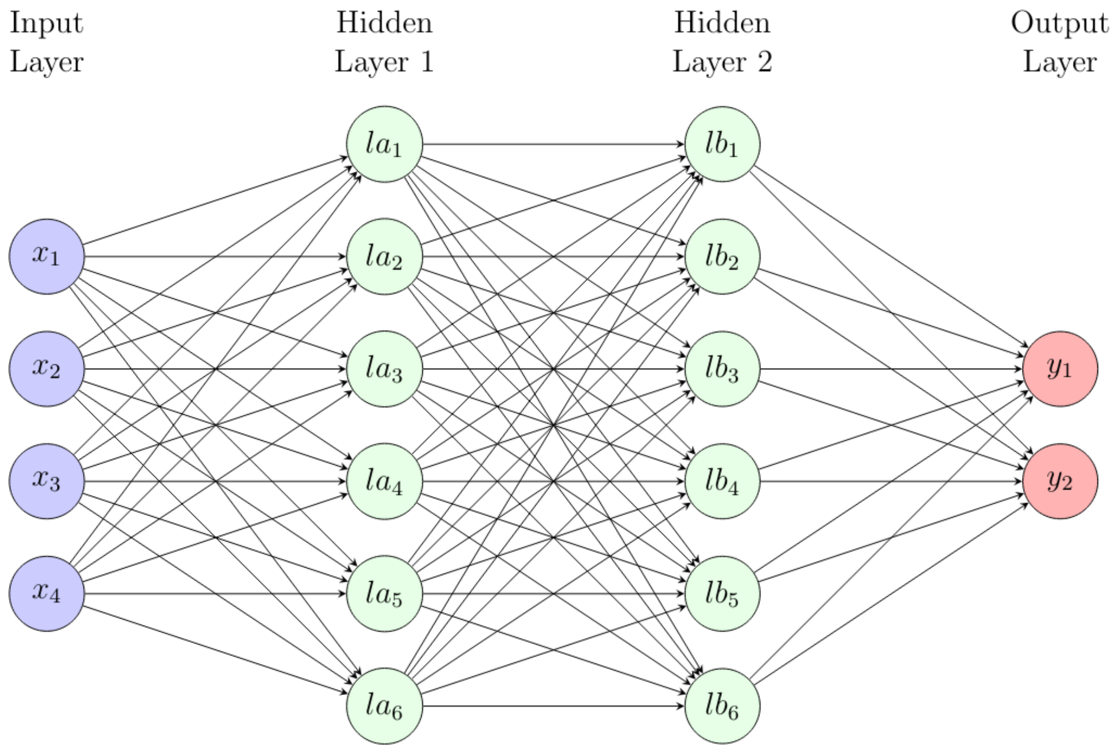
1. Initialize neural network with a fixed set of random weights.
2. Pass a source sample through the network with a high learning rate.
3. Record network parameters post backpropagation. This forms the representation of the source sample.

$$s_1 \rightarrow \begin{bmatrix} w_{11} \\ \vdots \\ w_{62} \end{bmatrix}$$

4. Reset the network to the same random configuration.
5. Repeat for all source and target samples

$$s_2 \rightarrow \begin{bmatrix} w_{11} \\ \vdots \\ w_{62} \end{bmatrix} \quad \ldots\ldots\ldots \quad s_m \rightarrow \begin{bmatrix} w_{11} \\ \vdots \\ w_{62} \end{bmatrix}$$

$$t_1 \rightarrow \begin{bmatrix} w_{11} \\ \vdots \\ w_{62} \end{bmatrix} \quad \ldots\ldots\ldots \quad t_n \rightarrow \begin{bmatrix} w_{11} \\ \vdots \\ w_{62} \end{bmatrix}$$



$$\begin{bmatrix} w_{11} & \cdots & w_{16} \\ \vdots & \ddots & \vdots \\ w_{41} & \cdots & w_{46} \end{bmatrix} \begin{bmatrix} w_{11} & \cdots & w_{61} \\ \vdots & \ddots & \vdots \\ w_{61} & \cdots & w_{66} \end{bmatrix} \begin{bmatrix} w_{11} & \cdots & w_{12} \\ \vdots & \ddots & \vdots \\ w_{61} & \cdots & w_{62} \end{bmatrix}$$

Class-wise Network Parameter Averaging (CNPA)

6. Aggregate network parameters for each class and compute the class-wise mean source parameter vectors

$$P_{d,c} = \frac{\sum_{i=1}^{n} p_i}{n}$$

$$where\ d\ and\ c\ represent\ the\ domain\ and\ class\ of\ the\ sample$$

$$and\ p_i\ are\ the\ network\ parameters\ for\ a\ sample\ from\ the\ said\ domain\ and\ class$$

7. Calculate the Euclidean distance between the source and target class-wise vector representations to quantify their dissimilarity

$$CNPA = \sqrt{\left(P_{source,\,0}\right)^2 - \left(P_{target,\,0}\right)^2} + \sqrt{\left(P_{source,\,1}\right)^2 - \left(P_{target,\,1}\right)^2}$$

Z. Zhang, Z. Jia, Gradsign: Model performance inference with theoretical insights, arXiv preprint arXiv:2110.08616 (2021)

Datasets used

- MIMII DG (Machine sound dataset for Domain Generalization)
  - Fan
  - Gearbox
  - Bearing
  - Slide rail
  - Valve

- GTZAN
  - Blues, Classical, Country, Disco, Hip-hop, Jazz, Metal, Pop, Reggae, and Rock

- Vehicle cabin booming noise
  - Ford Focus
  - Opel Vectra
  - **Ford Mondeo**

Results

Source Dataset	Distance Measures					Target Scores	
	L1	L2	MMD	CORAL	CNPA	Target AUROC	Target APS
Gearbox	7149.5	54.37	0.1104	88.33	255.0	0.49	0.50
Valve	9520.9	69.67	0.1918	72.36	271.2	0.62	0.62
Fan	10657.8	77.44	0.2334	246.8	276.6	0.56	0.55
Slider	10917.3	77.80	0.2427	86.57	269.0	0.62	0.61
Bearing	12231.1	86.85	0.2977	113.3	282.4	0.73	0.71
GTZAN-03	24696.3	171.0	1.034	222.9	334.3	0.74	0.73
GTZAN-85	26018.3	179.0	1.120	247.8	337.4	0.62	0.62
GTZAN-72	26372.3	181.0	1.150	228.8	336.6	0.65	0.65
Vectra	1331.9	15.24	0.008019	6.814	180.2	0.95	0.92
Focus	1469.7	16.77	0.01072	7.531	171.9	0.95	0.94
Mondeo	1124.7	13.21	0.003241	6.853	119.3	0.99	0.98

Distance Measure	Correlation coefficient
L1	-0.496
L2	-0.497
MMD	-0.337
CORAL	-0.628
CNPA	-0.738

Final remarks

- The proposed approach provides a principled framework for source domain selection by considering not only the intrinsic disparities between datasets but also their compatibility with the model architecture.

- It gives a combined assessment of domain shift and transferability facilitating appropriate source domain selection.

- A future application of interest is the transfer from ICE vehicles to electric vehicles as some problems such as booming (ICE) and whine (EV) bear resemblance from a fault modelling perspective.

Thank You!

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