

# CV

## AmirEhsan Khorashadizadeh

### PERSONAL INFORMATION

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Personal Webpage

GitHub

Google Scholar

### EDUCATION

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<b>Ph.D. In Data Science</b> University of Basel CURRENT GPA: <b>6.0/6.0</b>	<b>Basel, Switzerland</b>  (2020 - Present)
<b>M.Sc. In Electrical Engineering</b> Sharif University of Technology OVERALL GPA: <b>18.52/20</b>	<b>Tehran, Iran</b>  (2018 - 2020)
<b>B.Sc. In Electrical Engineering</b> University of Tehran OVERALL GPA: <b>17.01/20</b>	<b>Tehran, Iran</b>  (2013 - 2018)

### RESEARCH INTERESTS

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- Generative Modeling
- Implicit Neural Representation
- Computational Imaging

### PUBLICATIONS

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- [1] AmirEhsan Khorashadizadeh, Anadi Chaman, Valentin Debarnot and Ivan Dokmanić. ‘FunkNN: Neural Interpolation for Functional Generation.’ International Conference on Learning Representations (ICLR 2023) (available on [OpenReview](#) and [Arxiv](#)).
- [2] AmirEhsan Khorashadizadeh, Sepehr Eskandari, Vahid Khorashadizadeh and Ivan Dokmanić. ‘Deep Injective Prior for Inverse Scattering.’ Under review in IEEE Transactions on Antennas and Propagation (available on [Arxiv](#)).
- [3] AmirEhsan Khorashadizadeh, Ali Aghababaei, Tin Vlašić, Hieu Nguyen and Ivan Dokmanić. ‘Deep Variational Inverse Scattering.’ European Conference on Antennas and Propagation (EUCAP 2023) (available on [Arxiv](#)).
- [4] Tin Vlašić, Hieu Nguyen, AmirEhsan Khorashadizadeh and Ivan Dokmanić. ‘Implicit Neural Representation for Mesh-Free Inverse Obstacle Scattering.’ 56th Asilomar Conference on Signals, Systems, and Computers 2022 (available on [Arxiv](#)).
- [5] AmirEhsan Khorashadizadeh, Konik Kothari, Leonardo Salsi, Ali Aghababaeiharandi, Maarten V. de Hoop and Ivan Dokmanić. ‘Conditional Injective Flows for Bayesian Imaging.’ Under review in IEEE Transactions on Computational Imaging (available on [Arxiv](#)).
- [6] Kothari, Konik, AmirEhsan Khorashadizadeh, Maarten de Hoop, and Ivan Dokmanić. ‘Trumpets: Injective flows for inference and inverse problems.’ Uncertainty in Artificial Intelligence (UAI 2021).
- [7] Amir Ehsan Khorashadi-Zadeh, Massoud Babaie-Zadeh, and Christian Jutten. ‘A Novel Pruning Approach for Bagging Ensemble Regression Based on Sparse Representation.’ IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP 2020).

## HONORS AND AWARDS

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- Ranked 4<sup>th</sup> among more than 15000 participants in the master of electrical engineering exam (2018)
- Ranked 183<sup>th</sup> among more than 200,000 participants in the national university entrance exam (2013)
- Semi-finalist in Iranian National Mathematics Olympiad (2012)
- Semi-finalist in Iranian National Computer Olympiad (2012)

## THESIS

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**M.Sc. thesis:** AmirEhsan Khorashadizadeh, “Pruning Machine Learning Models by Sparse Representation”, Dept. Elect. Eng., Sharif University of Technology, Tehran, Iran. (2019-2020)  
Supervisor: Prof. Massoud Babaie-Zadeh

**B.Sc. thesis:** AmirEhsan Khorashadizadeh, “Speaker Recognition System”, Dept. Elect. Eng., University of Tehran, Tehran, Iran. (2017)  
Supervisor: Prof. Mohammad Ali Akhaee

## TECHNICAL SKILLS

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- **Programming**
  - Python
- **Tool/Software**
  - Pytorch, Tensorflow, Matlab, Git
- **Language Proficiency**
  - Persian: Mother tongue
  - English: Fluent
- **Publishing & Editing Software**
  - L<sup>A</sup>T<sub>E</sub>X and Microsoft Office

## RESEARCH EXPERIENCE

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- **Deep generative models for solving inverse problems** SADA Lab (2020-2022)
  - **Trumpets: Injective Flows for Inference and Inverse Problems:** We devised a novel class of deep generative models called injective normalizing flows. Injective flows are invertible deep neural networks which benefit from the advantages of regular normalizing flows; fast inverse and tractable logdet of Jacobian computations, while, unlike regular normalizing flows which have a latent space with the same dimension as the data space, provide a low dimensional latent space and produce a low-dimensional manifold in the high-dimensional data space. We have shown that the proposed model is a natural choice for solving ill-posed inverse problems, from image super-resolution and image in-painting to computational imaging problems.
  - **Conditional Injective Flows for Bayesian Imaging:** Most deep learning models for computational imaging regress a single reconstructed image, for example, by using UNet, which takes the measurements as input and returns one single reconstruction as output. In practice, however, ill-posedness, nonlinearity, model mismatch, and noise often conspire to make a single reconstruction misleading or insufficient. We proposed a new family of conditional deep generative models based on injective normalizing flows, which can effectively estimate the posterior distribution instead of producing a single reconstruction. By having access to the posterior, we are able to generate posterior samples, compute MAP and MMSE estimates and evaluate uncertainty quantification. We showed our model can efficiently generate physically meaningful posterior samples and uncertainty quantification over various inverse problems, from image restoration tasks (denoising, inpainting, super resolution and random masking) to imaging problems.
  - **Deep Variational Inverse Scattering:** Inverse medium scattering solvers generally reconstruct a single solution without an associated measure of uncertainty. This is true both for the classical iterative solvers and for the emerging deep learning methods. But ill-posedness and noise can make this single estimate inaccurate or misleading. In this project, we propose U-Flow, a Bayesian U-Net based on conditional normalizing flows, which generates high-quality posterior samples and estimates physically-meaningful uncertainty. We show that the proposed model significantly outperforms the recent normalizing flows

in terms of posterior sample quality, while having comparable performance with the U-Net in point estimation.

- **Deep Injective Prior for Inverse Scattering:** In electromagnetic inverse scattering, we aim to reconstruct object permittivity from scattered waves. In this project, we propose a new data-driven framework for inverse scattering based on deep generative models. We model the target permittivities by a low-dimensional manifold which acts as a regularizer and learned from data. Unlike supervised methods which require both scattered fields and target signals, we only need the target permittivities for training; it can then be used with any experimental setup. We show that the proposed framework significantly outperforms the traditional iterative methods especially for strong scatterers while having comparable reconstruction quality to state-of-the-art deep learning methods like U-Net.

- **Implicit Neural Representation**

[SADA Lab \(2021-2022\)](#)

- **FunkNN: Neural Interpolation for Functional Generation:** Existing MLP-based architectures generate worse samples than the grid-based generators with favorable convolutional inductive biases. Models that focus on generating images at different scales do better, but employ complex architectures not designed for continuous evaluation of images and derivatives. We take a signal-processing perspective and treat continuous image generation as interpolation from samples. Indeed, correctly sampled discrete images contain all information about the low spatial frequencies. The question is then how to extrapolate the spectrum in a data-driven way while meeting the above design criteria. Our answer is FunkNN—a new convolutional network which learns how to reconstruct continuous images at arbitrary coordinates and can be applied to any image dataset. Combined with a discrete generative model it becomes a functional generator which can act as a prior in continuous ill-posed inverse problems. We show that FunkNN generates high-quality continuous images and exhibits strong out-of-distribution performance thanks to its patch-based design. We further showcase its performance in several stylized inverse problems with exact spatial derivatives.
- **Implicit Neural Representation for Mesh-Free Inverse Obstacle Scattering:** Implicit representation of shapes as level sets of multilayer perceptrons has recently flourished in different shape analysis, compression, and reconstruction tasks. In this project, we introduce an implicit neural representation-based framework for solving the inverse obstacle scattering problem in a meshfree fashion. Additionally, we propose a deep generative model of implicit neural shape representations that can fit into the framework. The deep generative model effectively regularizes the inverse obstacle scattering problem, making it more tractable and robust, while yielding high-quality reconstruction results even in noise-corrupted setups.

- **Single-cell RNA-seq in drug discovery**

[Roche \(2022\)](#)

In this project, I as a part of a team deployed several machine learning techniques for single-cell drug discovery. We used random forest classifier to identify the cell type that has more distinguishable cells between healthy and inflamed.

- **Normalizing Flows for Out of Distribution Detection**

[SADA Lab \(2021\)](#)

Normalizing flows are deep generative models that provide an exact likelihood besides convenient sample generation by using a set of bijective transformations. The provided likelihood can be deployed to detect out of distribution samples; however, these models often assign a higher likelihood to outlier samples than the data used for maximum likelihood training. In this work, we studied the potential reasons why normalizing flows fail to detect out-of-distribution samples.

- **Sparse Representation for Pruning of Learning-based Models**

[Sharif University \(2019-2020\)](#)

Learning-based models, including classifiers and regressors, often suffer from over-fitting and large memory and computation. Different methods have been proposed to prune these models to reduce the size and improve the generalization. In this project, we leveraged sparse representation as a powerful method for pruning several machine learning models, including bagging ensemble regressors and classifiers.

- **Face and Speaker Recognition**

[University of Tehran \(2017\)](#)

In this project, we analyzed the performance of different models and techniques for speaker and face recognition.

- We analyzed joint factor analysis and i-vector feature extraction for speaker recognition.

- We used CNN-based face detection and transfer learning technique for few-shot face recognition.
- We studied the existing methods for out-of-distribution detection for face and speaker recognition.

## PROFESSIONAL EXPERIENCE

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- **Shell Pistachio Recognition** Jharfabin (2019)

Design & implement a system to distinguish open and closed pistachio nuts images. A variety of state-of-the-art image classifiers are analyzed over the provided dataset by the company.

- **Image Registration** Sensifai (2019-2020)

Design & implement image registration part of multi-camera object detection, tracking, and re-identification system funded by Eberle Design Inc (EDI).

- **Video Synopsis** Sensifai (2019)

Design & implement of a system that superimposes objects on a stationary background and simultaneously displays objects that have been at different times. In this project, YOLO has been used for the object detection task.

## RELEVANT COURSES AND GRADES

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- **Graduate**

- Pattern Recognition: (17.3)
- DeepLearning: (20/20)
- Statistical Learning: (19.4/20)
- Discrete-time Signal Processing (DSP): (16.6/20)
- Computer Vision: (19/20)
- Speech Processing: (19/20)
- Numerical Optimization: (20/20)
- Model- and Learning-Based Inverse Problems in Imaging: (6/6)
- Scientific Writing and Science Communication: (6/6)

- **Undergraduate**

- Calculus: (19.25/20)
- Differential Equations: (20/20)
- Numerical Computations: (19.9/20)
- Engineering Mathematics: (18/20)
- Engineering Probability & Statistics: (18.5/20)
- Linear Control Systems: (19.1/20)
- Systems Analysis:(18.3/20)
- Communications Systems: (17.5/20)