DAT255

Deep learning engineering

PROJECT CATALOG

During the course, you will get to work on a relatively large-scale project using the course's theory, techniques, and tools. The projects are designed to address a broad selection of areas of great societal interest, such as medicine and health, energy, the environment, surveillance, and fundamental science.

Alexander S. Lundervold
Deep learning engineering

Alexander S. Lundervold, **Version 3.3**
03.02.23

Western Norway
University of
Applied Sciences

About the course projects 3
Media and communication 4
Deep learning and audio processing 5
Sentiment analysis from social media 6
Analyzing patent applications using NLP 7
Retail 8
Personalized fashion recommendations 9
Health and medicine 10
Chest X-rays 11
Deep learning and pathology 12
Segmentation from brain MRI 13
Analyzing EEG data using deep learning 14
Drug discovery 15
fastMONAI for medical image analysis 16
Food recognition from images 17
Fundamental science 18
Search for new physics at the Large Hadron Collider 19
Method development 20
Data augmentation in computer vision 21
Deep learning for tabular data 22
Uncertainty and Bayesian deep learning 23
Self-supervised learning in computer vision 24
Remote sensing and surveillance 25
Deep learning and satellite data 26
Food production: Fishing and agriculture 27

An exploration of the world of *AgTech* 28

Subsea imaging in fishing and shipping 29

Energy 30

Inspecting power systems using computer vision 31

About the course projects

How it works

- Browse through the projects in this catalog and select the one you find the most interesting. Note that these are very brief project descriptions. More details will be provided after the project selection phase.
- Several students may select the same project, and you may team up (or not).
- It is possible to suggest your own project. In that case, you must write a one-page description like the project descriptions in the catalog, and the course lecturer must approve your suggestion. This is to ensure relevance and feasibility. For example, if you've already decided on a bachelor's or master's thesis topic, it could be natural to think about a possible project relevant to your thesis. Exploring Kaggle and other similar sources of data and tasks can help you find exciting and feasible problems.

What's expected

At the project deadline, you'll hand in source code, documentation, and potentially other artifacts from your work. Precisely what is partly up to you:

- **Required**: A link to a well-documented online Git repository containing all the code and documentation necessary to understand and reproduce your work, including code to create and run any applications you've made. You also must explain the larger context to which your work belongs, for example, in a readme file in your repository.
- **Recommended**: An application running in the cloud or that can be installed on a computer or a mobile device. The setup from Module 2 will get you quite far (Gradio + HuggingFace Spaces or similar), but feel free to be more ambitious.
- **Recommended**: A blog post explaining the background of your project, its objectives, what methods and data you used, and what you achieved. The post should target a broad audience. For example, other software engineering students with little knowledge of the application domain and the relevant methods. fastpages is a good blogging solution.

Notes

As you'll see from the project catalog, specific course modules are more relevant to some projects than others. For example, some projects are based on natural language processing (NLP), a module that comes relatively late in DAT255. Therefore, it is essential to skip ahead to start your project as soon as possible. But make sure that by the end of the course, you've worked sufficiently hard on every module, even those less relevant to your chosen project. The DAT255 mini-projects can help you achieve that: make sure to work on mini-projects that belong to a different area of the course than your project work.

Media and communication

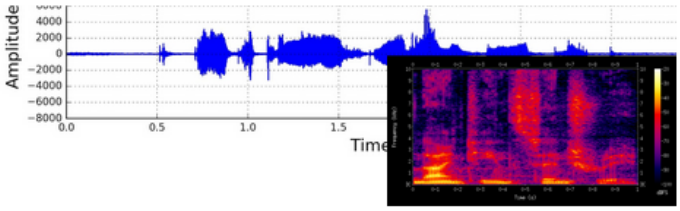
Modern media and communication are highly technologically driven and are increasingly influential in our daily lives, from how we communicate and learn from each other to our worldview and politics.

Western Norway University of Applied Sciences

Deep learning and audio processing

Introduction

Systems able to recognize sounds directly from audio recordings are widely applicable. In this project, you'll attempt to create an audio tagging system by first extracting image representations of audio clips and then using computer vision-based classification models. You can consider constructing your system using a relatively large-scale competition data set and then evaluate it on its ability to recognize and distinguish more specialized sounds on locally generated recordings.



Goals

1. Investigate and construct models for automatic audio tagging of noisy recordings.
2. Adapt this to smaller data sets of audio recordings, either by using a setup motivated by your above findings or by transfer learning.
3. Construct an audio tagging application.

Methods and materials

To achieve Goal 1 of the project, you can, for example, use the FSDKaggle2018 used in the Freesound General-Purpose Audio Tagging Challenge on Kaggle. There are 41 categories of audio clips, and the goal is to classify each clip. For the second objective, you can look for a data set on your own or construct one yourself.

As part of the project, you should investigate ways to do data augmentation for audio.

You'll make use of a variety of Python audio libraries, e.g., librosa. You should also look into fastaudio, a library built on top of fastai. To construct the application, you're free to use any solution you know or want to investigate. A natural starting point is the deployment solutions used in the fastai course, or, if you want to be more ambitious, the material from Module 9 based on TensorFlow Extended (TFX).

Consider not converting audio to images but instead setting up an audio classification framework that operates on audio representations of the data.

Sentiment analysis from social media

Introduction

A goal of sentiment analysis is to extract the opinion expressed by pieces of text, which is a major area of applied natural language processing. In this project, you will perform sentiment analysis on multiple different existing data sets and construct your own data set by scraping Twitter and producing sentiment labels for training supervised classification models. You are encouraged to combine multiple data sets to train a single model and to explore using transfer learning to increase classification performance.

The project will lead to solid experience in data preparation for sentiment analysis based on the tools of fastai and experience from various application domains.

Goals

- Construct sentiment analysis models based on the NLP techniques of HuggingFace and fastai.
- Gain solid experience with the objectives, challenges, and pitfalls of this approach to sentiment analysis.

Methods and materials

A major part of the project is to investigate a variety of data sets, as this is the best way to gain solid, generalizable experience. Here are some existing data sets to get you started (you should look for additional data sets yourself):

- Amazon Review Data, https://nijianmo.github.io/amazon/index.html. See also URLs.AMAZON_REVIEWS and URLs.AMAZON_REVIEWS_POLARITY in fastai
- Twitter US Airline Sentiment, https://www.kaggle.com/crowdflower/twitter-airline-sentiment.
- Multi-Domain Sentiment Dataset, http://www.cs.jhu.edu/~mdredze/datasets/sentiment
- OpinRank Review Dataset, http://archive.ics.uci.edu/ml/datasets/opinrank+review+dataset.

You are encouraged to construct your own data set by scraping one or more relevant internet sources. The Python libraries Beautiful Soup and Scrapy are worth investigating. Twitter is a relatively easy source for data, perhaps combined with efficient techniques for data labeling, for example, Snorkel.

Analyzing patent applications using NLP

Introduction

Natural language processing (NLP) can automate the extraction of essential information from the text of a patent application, such as the claims, the background, and the description of the invention. This can include identifying relevant technical terms and concepts, classifying the invention according to predetermined categories, and identifying potential prior art references. NLP can also identify patterns and trends in the data, such as identifying common themes among a group of applications or identifying which types of inventions are most likely to be granted patents. NLP can be used to construct tools for searching and summarizing patent applications, easing communication and collaboration between patent examiners. Additionally, using generative NLP models, one can also build tools that can assist in the writing of patent applications.,

Goals

- Construct sentiment analysis models based on the NLP techniques of HuggingFace and fastai.
- Gain solid experience with the objectives, challenges, and pitfalls of this approach to sentiment analysis.

Methods and materials

Jeremy Howard's approach to the Kaggle challenge U.S. Patent Phrase to Phrase Matching can form a natural starting point. From the description of the competition:

> *In this competition, you will train your models on a novel semantic similarity dataset to extract relevant information by matching key phrases in patent documents. Determining the semantic similarity between phrases is critically important during the patent search and examination process to determine if an invention has been described before. For example, if one invention claims "television set" and a prior publication describes "TV set", a model would ideally recognize these are the same and assist a patent attorney or examiner in retrieving relevant documents. This extends beyond paraphrase identification; if one invention claims a "strong material" and another uses "steel", that may also be a match. What counts as a "strong material" varies per domain (it may be steel in one domain and ripstop fabric in another, but you wouldn't want your parachute made of steel).*
>
> *Can you build a model to match phrases in order to extract contextual information, thereby helping the patent community connect the dots between millions of patent documents?*

- U.S. Patent Phrase to Phrase Matching, https://www.kaggle.com/competitions/us-patent-phrase-to-phrase-matching
- Patent text: code, data, and new measures, https://zenodo.org/record/3515985

You are encouraged to explore other sources of data.

Retail

Retail is the sale of goods and services to consumers and is a 26 trillion U.S. dollar industry. It is heavily impacted by the integration of computer technology, particularly in e-commerce and data analysis. Online retailers use technology to manage inventory, process payments, and track customer behavior. Machine learning is increasingly being used to improve these processes and provide customers with a more personalized shopping experience.

Personalized fashion recommendations

Introduction

Personalized fashion recommendations can help individuals find clothing and accessories that fit their unique style, body shape, and preferences. By considering a person's characteristics and needs, personalized recommendations can save time and effort in the shopping process and increase the likelihood that a person will be satisfied with their purchase. Additionally, personalized recommendations can help individuals discover new styles and fashion trends they may not have otherwise considered.

Goals

Here are some possible goals you may consider aiming for:

- First, explore some of the current trends in the intersection of machine learning and the retail sector.
- Create a recommendation system based on data from customers' previous transactions
- Evaluate the ability of the system to predict future purchases.
- Construct a system able to determine which images are of the same product.

Methods and materials

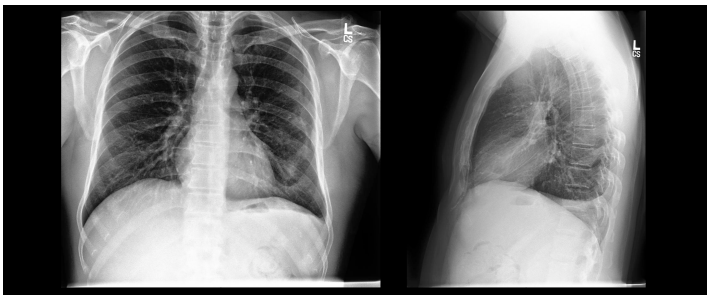
- https://www.kaggle.com/c/h-and-m-personalized-fashion-recommendations/overview
- https://www.kaggle.com/competitions/shopee-product-matching/overview

Health and medicine

Healthcare is one of the economy's largest sectors, and it is subject to tremendous technological progress. An aging population and increasing expectations of modern medicine have led to an immense interest in the field of "medical AI." It promises to transform the sector and lead to a much-improved healthcare system, where the treatment of each patient is informed by the vast collection of data gathered by an increasingly powerful set of technologies.

Chest X-rays

Introduction



Identifying and assessing structures in the lung from X-ray scans of the chest is an essential task across multiple diseases involving the lungs and upper abdomen, e.g., lung cancer, infections, pneumonia, broken ribs, and more. X-ray images can provide a detailed view of the lungs and surrounding structures, making it possible to detect, analyze, monitor, and assess treatment response. Computer-aided diagnostic tools addressing chest X-rays are important in medical imaging, possibly increasing speed, accuracy, consistency, and cost-effectiveness.

Goals

- Create a deep learning system to detect one or more of 14 conditions directly from one or more chest X-rays (see data link below for details).
- Investigate and apply techniques for “Explainable AI.”

Methods and materials

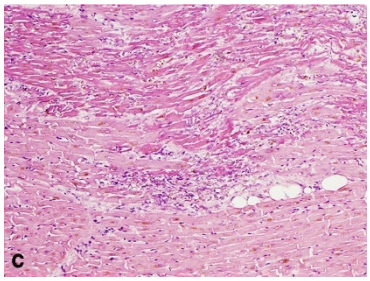
- https://stanfordmlgroup.github.io/competitions/chexpert
- https://physionet.org/content/mimic-cxr-jpg/2.0.0/
- https://cloud.google.com/healthcare-api/docs/resources/public-datasets/nih-chest
- https://github.com/ieee8023/covid-chestxray-dataset
- https://data.mendeley.com/datasets/jctsfj2sfn/1

You should look for additional data sources as part of the project work.

Deep learning and pathology

Introduction

Every treatment and cure begins with a diagnosis. Every year, pathology laboratories and pathologists in Norway make several hundred thousand diagnoses on tissue samples. The pathology reports are a prerequisite for treating and curing almost all cancers and many other diseases.



Pathology is currently undergoing a digital transformation: rather than inspecting samples on glass slides using conventional microscopy, the slides are digitized, and the microscope is turned into a virtual microscope. This leads to easier management and sharing of pathology information and opens the door to a more computer-driven interpretation process. In fact, a whole new field, “computational pathology,” is emerging, enabling large-scale computer-aided diagnosis.

Goals

1. Explore the topic of digital pathology, focusing on the potential for computer-aided interpretation and diagnosis.
2. Perform hands-on experiments on real data (some data sources are listed below).

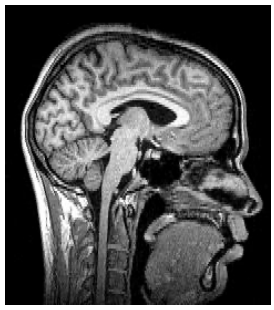
Methods and materials

Here are a few data sources to get you started. Note that some of these are data sets from various challenges posed to the community. It is possible to use the data without tackling the specific challenge of the organizers.

- https://www.dropbox.com/s/jka111c16q8cn6x/PNAS-images.zip & https://www.dropbox.com/s/zogil8mxr2p9ajy/pathfusion.zip
- https://www.kaggle.com/c/histopathologic-cancer-detection
- https://segpc-2021.grand-challenge.org/SegPC-2021/
- https://wiki.cancerimagingarchive.net/display/Public/C_NMC_2019+Dataset%3A+ALL+Challenge+dataset+of+ISBI+2019
- https://www.kaggle.com/c/data-science-bowl-2018
- https://patchcamelyon.grand-challenge.org

Segmentation from brain MRI

Introduction



Partitioning an image into parts or regions is called *image segmentation*. Examples include separating the foreground from the background, identifying what category of object each pixel in an image belongs to (*semantic segmentation*), or identifying parts of an image that shares some meaningful similarity. As you'll see in the course, segmentation is one of the core tasks in computer vision. It is also essential in medical imaging and has been called the "holy grail of medical image processing." Accurate segmentation of objects of interest in medical images allows for precise localization, quantification (e.g., tumor volume and growth), and much more.

Goals

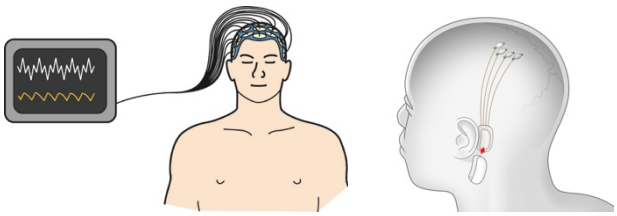
- Collect a large set of 3D head MRI recordings that have been processed using automatic segmentation software.
- Extract the mid-sagittal slices of the 3D MRI images and the corresponding masks containing delineations of brain structures.
- Focus on a specific brain structure, e.g., the corpus callosum. Extract the corresponding binary (or three-to-four class) segmentation masks.
- Train a 2D computer vision model to automatically segment the relevant region(s) directly from a mid-slice image.
- Investigate the method's robustness across various data sets sourced from a heterogeneous set of subjects, MRI scanners, and MRI protocols.
- As a bonus objective, try using fastMONAI to construct a full 3D segmentation model.

Methods and materials

- You may use images from the IXI and ADNI datasets. The course lecturer has already processed these images using the segmentation software FreeSurfer 7.1.1, and the resulting masks can be used in this project.
- In addition to the computer vision parts of DAT255, you'll learn about various other topics, tools, and concepts, including MRI, the NiFTi-1 data format, nibabel, FreeSurfer, ITK-SNAP

Analyzing EEG data using deep learning

Introduction



EEG, or electroencephalography, is a non-invasive method of measuring the brain's electrical activity. It is important in medicine because it allows doctors to diagnose and monitor various neurological conditions, such as epilepsy, brain tumors, and sleep disorders. Additionally, EEG can be used to evaluate brain function in patients who have suffered a head injury or stroke and to monitor brain activity during surgery. It also plays a crucial role in the research of brain function and disorders.

Deep learning has seen some use in the analysis of EEG data. For example, models trained on EEG data from patients with epilepsy can be used to identify patterns in the EEG signals indicative of seizures, allowing for earlier and more accurate detection. Similarly, one can classify sleep stages, which can help diagnose sleep disorders.

Goals

Some possible goals include:

- Explore ways to use deep learning with EEG data. For example, they can deal with the signals directly in their 1D form or treat them as 2D images.
- Create a system that can classify EEG recordings as either normal or containing signs of epileptic seizures.
- Classifying motor activity from EEG signals (which is an essential task for brain-computer interfaces.)

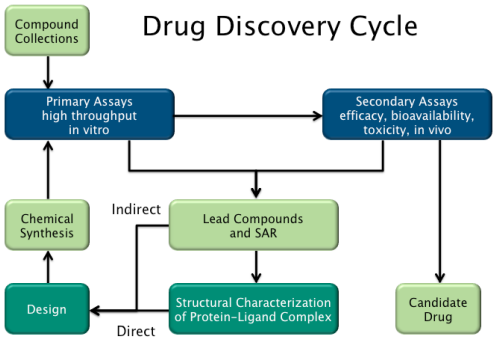
Methods and materials

- https://www.kaggle.com/competitions/grasp-and-lift-eeg-detection/overview
- https://openneuro.org/datasets/ds003775/versions/1.2.1
- https://openmiir.github.io/
- https://github.com/meagmohit/EEG-Datasets

You are encouraged to explore other data sources as part of the project.

Drug discovery

Introduction



The development of new drugs takes 15--20 years and is estimated to cost an average of 4 billion US dollars per drug. Modern drug discovery and development usually follow a set of systematic procedures, often starting with a validated biomolecular target for which one tries to find a modulator (i.e., a drug). For many years machine learning has played a role in drug discovery. In recent years modern machine learning techniques have been applied to all stages, from initial target discovery and compound screening to the analysis of pathology data during clinical development. There are strong indications that such techniques can speed up drug development and discovery processes, impacting the entire drug discovery process. In this project, you'll perform some hands-on experiments related to a crucial part of many drug development pipelines: e.g., predicting the affinity and activity of a drug candidate against a target.

Goals

- Explore the fascinating world of drug discovery. The exploration will quickly lead you deep into biology and chemistry. However, depending on your background, sticking to a "shallower" level is OK, focusing on obtaining the understanding necessary to perform the hands-on experiments.
- Construct predictive models based on one or more of the data sources linked below. These are already heavily preprocessed and prepared.

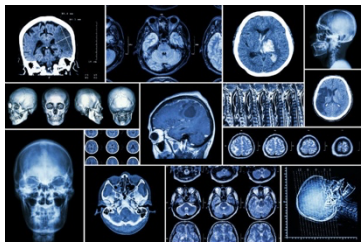
Methods and materials

- Data source #1: http://www.bioinf.jku.at/research/lsc/index.html
- Data source #2: https://link.springer.com/article/10.1186/s13321-017-0226-y

You are encouraged to explore other data sources as part of the project.

fastMONAI for medical image analysis

Introduction



In our research group, we have developed an open-source extension of the powerful fastai deep learning library to support tasks related to three-dimensional imaging (classification, regression, segmentation), incorporating elements from the MONAI library (https://monai.io) and TorchIO (https://torchio.readthedocs.io/).

We call it **fastMONAI,** and it is openly available via https://fastmonai.no/ and https://github.com/MMIV-ML/fastMONAI.

In this project, you will explore the use of the library for various medical imaging tasks using 3D data: binary, multi-class, and multi-label classification, regression, and segmentation, across a range of organs and types of images.

Goals

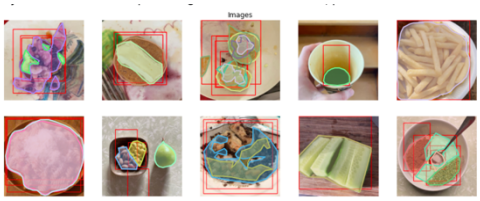
- Explore the world of medical imaging. Gain hands-on experience solving core tasks using deep learning.
- Get to know the fastMONAI library and other powerful deep learning frameworks for medical imaging.

Methods and materials

- MedNIST v2: https://medmnist.com/
- Medical Segmentation Decathlon: http://medicaldecathlon.com/

Food recognition from images

Introduction



Computer vision **based on deep learning can potentially** revolutionize **how we track** food intake. By **constructing a system that can automatically** recognize food from pictures, the process of logging food intake becomes much simpler and more efficient. **The information about what was consumed** can then be linked to databases containing information about the calorie content, macronutrient composition, and other important nutritional data for each food item.

Individuals can **then** gain a much deeper understanding of the foods they consume and their impact on their overall health**, helping them make** more informed decisions about what they eat and **providing** a more comprehensive picture of their daily caloric intake. It can also have numerous personal benefits**,** such as helping people lose weight, achieve specific fitness goals, or simply lead a healthier lifestyle.

Such a system could also have medical benefits. For example, doctors and nutritionists could use this information to better understand a patient's eating habits and make recommendations accordingly. In short, the use of computer vision to recognize food from pictures can have a significant positive impact on personal and medical health.

Goals

- Construct a system that can take an image of a set of food items as input and output the individual food items present in the image.
- Explore the possibilities such a system can have for personal health.

Methods and materials

- https://www.aicrowd.com/challenges/food-recognition-benchmark-2022
- https://www.frontiersin.org/articles/10.3389/fnut.2022.875143/full
- https://www.myfoodrepo.org/
- https://github.com/topics/food-recognition

Fundamental science

In recent years, deep learning has played a vital role in the search for solutions to many critical challenges in science. As a result, it is increasingly becoming part of the standard research toolkit of fundamental science. The scope is broad, from applications to protein folding, the search for dark matter, and the design of scientific experiments, to artificial neural networks acting as inspiration for neuroscience, i.e., the study of biological neural networks.

Search for new physics at the Large Hadron Collider

The Standard Model of Particle Physics (SM) describes the results of decades worth of particle physics experiments with a quantitative agreement which is truly excellent,[1] and no observations in such experiments are in significant disagreement with the model. There are, however, other observations, mainly from astrophysics, which clearly disagree with the SM, even though physicists believe that it should be possible to include these observations in the same theoretical framework. Such observations include the existence of dark matter and the fact that our universe is made of only matter and not equal parts matter and anti-matter. Current particle physics experiments are thus actively searching for observations that do not agree with the SM to find out how the model can be extended.

The presently largest particle physics experiments use the Large Hadron Collider (LHC) at CERN. In this project, you will use a small subset of the data recorded by the ATLAS detector to take part in the search for new physics. Most of the work will be done using simulated data which has the advantage that the underlying physics process is known for certain. Furthermore, the use of simulated data also allows testing the effect of a hypothetical extension of the SM.

Goals

- Create a classifier that can discriminate between SM physics processes and a particular extension of the SM (introduction of a new particle called Z').
- Measure the mass of the Z' particle in a simulated data set.
- Run the classifier on detector data to check for the presence of Z'.

Methods and materials

In the project's training and model development phase, you will use simulated data representing both SM processes and processes, including Z', with several possible values of its mass. The data format will be tabulated data in hdf5 file format.

Testing of your model will be done with simulated data, including a Z' with an unknown mass (not necessarily one of the masses in the training sample) and detector data recorded by ATLAS.

To construct the classifier, you are free to use any solution you find useful. Simple but probably effective methods include decision trees (random forest, BDT, …) and fully connected neural networks. However, it would be interesting to explore other alternatives as well.

Interested parties

The ATLAS research group at HVL:

- Trygve Buanes
- Therese Sjursen
- Steffen Mæland

Method development

There are many methodological challenges in deep learning and, therefore, opportunities to bring new tools, techniques, and knowledge into the field. Challenges include deep learning model's insatiable appetite for high-quality training data, the difficulty of incorporating domain knowledge into the models, the general lack of theory that can explain why one model is better than another, difficulties using general principles from the best practices of software engineering, explainability, and much more.

Data augmentation in computer vision

Introduction

As you've seen, a well-designed data augmentation setup is crucial for the efficient use of training data in deep learning. For image-based problems, several standard methods augment the training set, e.g., rotations, flips, translation, and more. However, there's a continuous stream of research and development aimed at creating more advanced, and ideally more powerful, data augmentation techniques. This project will explore these developments and provide a careful setup for evaluating the many methods: their strengths and weaknesses. It will also attempt to clarify what problems and situations fit with what data augmentation techniques and assist other developers in their choice and design of data augmentation setups.

Goals

- Explore the many existing techniques for data augmentation in deep learning for computer vision
- Design an experimental setup where you can evaluate the effect of applying these methods on a fixed set of data sets and problems.
- Create a library, or at least some very well-thought-out examples, that make it easy for others to reuse what you've done in this project on their own image data.

Methods and materials

- Data: The image data sets are listed under "External datasets" in fastai. For example, the IMAGENETTE data set.
- Methods: through the fastai course and library, you have been exposed to some basic data augmentation techniques (rotation, flips, image intensity variation) and some more advanced methods (MixUp, CutMix, and more). A substantial part of this project will be to explore, try, and perhaps extend what's out there for data augmentation in computer vision.

Deep learning for tabular data

Introduction

Module 6 of the course (chapter 9 of the textbook) deals with using deep learning methods for tabular data via so-called embeddings. It shows that it is possible to create high-performing neural network-based models for tabular data as an alternative to the much more standard approach based on other machine learning models (especially tree-based models like random forest and gradient-boosted trees).

This project aims to explore when and how neural networks provide reasonable alternatives to tree-based models when dealing with tabular data. It should be based on multiple experiments with various large tabular data sets. The different approaches must be compared using a reasonable evaluation setup (predictive performance, training time, inference time and requirements, explainability, etc.).

Goals

- Explore the use of neural networks for tabular data sets. Try to figure out in what situations it makes sense to use neural networks rather than more “standard” machine learning models for tabular data.

Methods and materials

- The methods covered in chapter 9 of the textbook will form the core part of the project. In addition, one can consider including other libraries for tree-based models, for example, LightGBM and XGBoost.
- Kaggle will be a good source for tabular data sets. A significant part of this project will be collecting and preparing multiple tabular data sets with various relevant characteristics.

Uncertainty and Bayesian deep learning

Introduction

Deep neural networks provide powerful predictive models across a wide variety of fields. However, they come with some inherent weaknesses, one of which is the lack of robust measures of uncertainty in most deep learning models. Standard models can often make surprising erroneous predictions with very high confidence, which is a major problem if the models are used to make important decisions, for example, in medicine and autonomous driving. What's needed are methods that can provide robust uncertainty measures without impacting predictive capability or leading to significant computational costs. One such method is called "Monte Carlo dropout" (MC dropout)

Goals

- Explore the area of Bayesian deep learning.
- Construct an implementation of MC dropout compatible with fastai
- Evaluate your implementation on a variety of data sets (see below for some examples)

Methods and materials

- CIFAR-10 and the PETS data set provide a good start.
- To move towards a specific application domain, you may consider using the CheXpert data set or any other relevant data set from an area you're interested in.

Self-supervised learning in computer vision

Introduction

Supervised learning, i.e., learning from labeled data, provides a mechanism to construct predictive models that can perform exceptionally well on specific tasks. However, the massive amounts of labeled data often needed to train accurate models means that many applications are, in practice, out of reach for supervised learning.

Self-supervised learning provides ways to use the vast amounts of *unlabeled* data one can typically get hold of to construct representations of underlying structures in the data. More specifically, ways to use labels that are somehow part of the input data rather than solely labels introduced in a separate (and costly) extra step.

Self-supervised learning has seen great success in natural language processing (NLP), where, e.g., the approach of constructing *language models* (models tasked with, e.g., predicting the next word of a given sentence—a task which can be set up with built-in labels by collecting vast amounts of texts and deleting words to construct model inputs) as backbones for, e.g., text classification models has had a profound impact (see, e.g., ULMFiT, BERT, RoBERTa, GPT-3, etc.).

This approach hasn't seen much use in computer vision, but that seems to be changing. Several recent results have shown that it is possible to construct self-supervised setups to make use of unlabeled data, ending in image classifiers that outperform models trained in a standard supervised learning fashion. There are indications that this can cause a small revolution in deep learning for computer vision in the coming years, particularly for the many application areas for which it is inherently difficult to produce large amounts of labeled data. One such field in medical imaging: there are vast amounts of unlabeled medical image data out there, but creating accurate and medically interesting labels is difficult and costly (caused by, among other things, issues related to privacy and the expertise required to assign labels).

Goals

- Explore existing setups for self-supervised learning in computer vision
- Evaluate the effects of including self-supervision in concrete cases: can you get increased predictive performance by incorporating unlabeled data?

Methods and materials

- You should start with relatively simple data sets.
- For compatibility with fastai, this is a possible starting point: https://keremturgutlu.github.io/self_supervised/

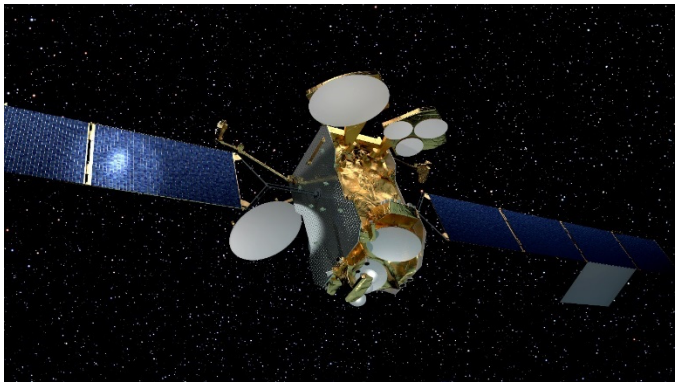
Remote sensing and surveillance

The goal of remote sensing is to detect and monitor objects or areas of interest from a distance by measuring their energy from a distance, for example, using aerial imaging or satellites. Slices of the electromagnetic spectrum are transformed into assessment and understanding of a system's current and future state. The field has many applications, e.g., climate, ocean, urban planning, population surveillance, farming, etc.

Western Norway
University of
Applied Sciences

Deep learning and satellite data

Introduction



The satellite industry is undergoing massive growth, fueled by (and leading to) a significant drop in the price of constructing and deploying satellites. As a result, their usage is regularly expanded to new domains and novel applications. The importance of methods able to extract actionable insight from data gathered from satellites is ever-increasing.

Goals

- Explore how computer vision systems based on deep learning can be used with satellite imaging to attack exciting problems and issues.
- Motivated by your exploration, perform hands-on experiments using actual satellite data.

Methods and materials

- The NORA MapAI competition: https://github.com/Sjyhne/MapAI-Competition
- https://stanfordmlgroup.github.io/projects/forestnet
- https://www.kaggle.com/competitions/understanding_cloud_organization/overview
- The various data sets prepared by SpaceNet: https://spacenet.ai
- Ship or iceberg? The Statoil challenge: https://www.kaggle.com/c/statoil-iceberg-classifier-challenge
- https://platform.ai4eo.eu/auto-ice
- https://github.com/robmarkcole/satellite-image-deep-learning

Food production: Fishing and agriculture

Food is a technological product, industrialized and dependent on a highly complex global supply system. It faces many challenging problems: population growth, urbanization, climate change, overproduction, inhumanity, lack of sustainability, unfair distribution, and more. Modern technologies based on, e.g., sensors, robotics, automation, and imaging plays an increasingly influential role in agriculture and aquaculture, leading to a great need for relevant tools, techniques, and skills.

Western Norway
University of
Applied Sciences

An exploration of the world of *AgTech*

Introduction

AgTech is a relatively vague term describing certain specific technologies applied to agriculture. It has been an area of great interest over the past decade. Arguably, the field hasn't yet produced significant breakthroughs in farming (depending on one's definition of AgTech), but the promise is great. Agriculture is one of the most important human endeavors. Considering the power and relevance of modern technologies like robotics, satellite imaging, drones, computer vision, and machine learning (and much more), it's no wonder that AgTEch companies attract significant investments and attention.

Goals

- Explore the field of AgTech. Its ambitions, methods, challenges, and current status
- Perform some hands-on experiments related to your explorations of the field and supported by data material available online. Some suggestions are listed below.

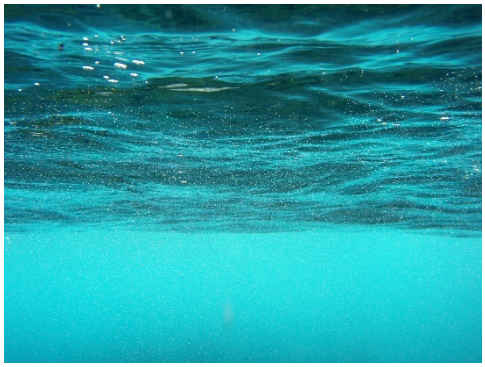
Methods and materials

Here are a few data sets that are relevant to the tools, techniques, and tricks you're learning in DAT255:

- https://www.kaggle.com/c/plant-pathology-2020-fgvc7
- https://vision.eng.au.dk/plant-seedlings-dataset or https://www.kaggle.com/vbookshelf/v2-plant-seedlings-dataset
- https://www.kaggle.com/jenny18/honey-bee-annotated-images
- https://stanfordmlgroup.github.io/projects/ognet/
- https://stanfordmlgroup.github.io/projects/forestnet/

Subsea imaging in fishing and shipping

Introduction



Marine imaging is a valuable tool across many industries, for example, fishing, shipping, and oil production. For example, imaging is used in fishing to locate and identify fish schools and map the seafloor to identify areas with high concentrations of fish or favorable habitats. This information can be used to optimize fishing operations and increase catch efficiency.

In shipping, subsea imaging can be used to survey and map the seafloor to identify potential hazards to navigation, such as shipwrecks, sunken debris, and underwater mountains. This information can be used to plan safe routes for ships and to identify areas that may need to be dredged to maintain safe depths for ships to navigate. Additionally, subsea imaging can be used to inspect and monitor the condition of underwater infrastructure such as pipelines, cables, and offshore structures.

This project will introduce you to the many use cases and specific challenges.

Goals

- Explore the current solutions and the possibilities for computer vision in underwater imaging.
- Gain hands-on experience creating predictive models using several different data sets representing some of the field's variations.

Methods and materials

- Marine fouling images. https://ieee-dataport.org/documents/marine-fouling-images
  Download data from here: Part1, Part2, Part3
- DeepFish: https://alzayats.github.io/DeepFish
- https://swfscdata.nmfs.noaa.gov/labeled-fishes-in-the-wild/
- https://www.kaggle.com/sripaadsrinivasan/fish-species-image-data

Energy

Obtaining, generating, transforming, transmitting, storing, distributing, and using energy are areas experiencing massive interest, as solving the world's energy problems is one of the major scientific and engineering challenges of our time. In anything from renewable energy and energy storage to building efficiency and carbon capture, modern computing tools and techniques play a central role.

Inspecting power systems using computer vision

Introduction

Drones enable visual inspection of power lines. Combined with computer vision and autonomous navigation, they can provide a cheap and accurate way to assess conditions and detect defects, even in remote or rugged areas. Drones equipped with high-resolution cameras can capture images of power lines from different angles, allowing for detailed inspections of the lines for any signs of damage or wear. Equipped with thermal sensors able to see “hot spots,” their utility is further expanded, enabling the detection of loose connections or other equipment failures.

The drone data can be transmitted in real-time to a remote monitoring station, allowing for real-time monitoring of the power lines and rapid response to any detected issues.

Goals

- Create a system to precisely locate power lines in images collected from drones.
- To broaden the project’s perspective, you can investigate ways to detect and classify power stations from aerial imagery.

Methods and materials

Here are some possible sources of data:

- PLD-UAV data set: https://github.com/SnorkerHeng/PLD-UAV
- OGNet data set: https://stanfordmlgroup.github.io/projects/ognet/. This is a data set of oil refineries. Still, the methods and experience you’ll obtain from studying this data set will be highly generalizable to similar problems (if you get a hold of labeled data).