Medical/Bio Research Topics Ⅰ: Week 12 (20 May 2025)

Hands-on AI Model Development: Model Architecture

인공지능 모델 개발 실습: 모델 구조

Automated Machine Learning (AutoML)

- Process of automating the end-to-end process of applying machine learning to real-world problems
- Aims to automate the time-consuming and challenging tasks involved in building machine learning models, thereby reducing the need for extensive domain expertise and allowing for more rapid experimentation and iteration

- General features
  - Data ingestion and preprocessing
    - Handles tasks such as data cleaning, formatting, and feature engineering, often automatically detecting the data types and applying appropriate transformations
  - Model selection
    - Explores different model architectures and algorithms that are suitable for the given problem and dataset
  - Hyperparameter tuning
    - Automatically tunes the hyperparameters of the selected models, which are configurations that can significantly impact model performance

- Model evaluation and validation
  - Evaluates the performance of the trained models using appropriate metrics and techniques (e.g., cross-validation or holdout sets)
- Model ensembling
  - May combine multiple models through ensembling techniques (e.g., stacking, bagging, or blending) to improve overall performance and robustness
- Model deployment
  - Deploys the best-performing model or ensemble for production use, often with automatic code generation and containerization for easy deployment

- Benefits
  - Efficiency
    - Reduces the time required to build and optimize models
  - Accessibility
    - Makes machine learning techniques accessible to users without extensive machine learning expertise
  - Performance
    - Often achieves competitive or superior performance compared to manual model tuning

- Popular AutoML libraries in Python
  - Primarily focused on automating the process of selecting traditional machine learning algorithms
    - TPOT (Tree-based Pipeline Optimization Tool) [http://epistasislab.github.io/tpot/; https://github.com/EpistasisLab/tpot]
    - AutoGluon [https://auto.gluon.ai/stable/index.html; https://github.com/autogluon/autogluon]
    - H2O AutoML [https://docs.h2o.ai/h2o/latest-stable/h2o-docs/automl.html; https://github.com/h2oai/h2o-3]
    - PyCaret [https://pycaret.org/; https://github.com/pycaret/pycaret]
    - Auto-sklearn [https://automl.github.io/auto-sklearn/; https://github.com/automl/auto-sklearn]

- Designed specifically for automating the process of neural architecture search and hyperparameter optimization for deep learning models
  - NNI (Neural Network Intelligence) [https://github.com/microsoft/nni]
  - AutoKeras [https://autokeras.com/; https://github.com/keras-team/autokeras]
  - Auto-PyTorch [https://www.automl.org/automl-for-x/tabular-data/autopytorch/; https://github.com/automl/Auto-PyTorch]
- Cloud-based services
  - Google Vertex AI [https://cloud.google.com/vertex-ai]
  - Microsoft Azure AutoML [https://azure.microsoft.com/solutions/automated-machine-learning]
  - Amazon SageMaker Autopilot [https://aws.amazon.com/sagemaker-ai/autopilot/]

- Limitations
  - Does not entirely replace the need for human oversight and expertise
  - Still requires input data, problem formulation, and guidance from domain experts to ensure appropriate model selection, interpretation, and deployment

TPOT

- AutoML library in Python that uses a genetic algorithm (GA) to explore the space of possible machine learning pipelines and optimize them
  - Starts with a population of random pipelines and iteratively evolves them through operations like mutation (modifying pipeline steps) and crossover (combining pipelines) to find the best-performing pipeline for the given dataset
  - Automatically constructs complex machine learning pipelines that may be difficult for human experts to design manually

- GA
  - Search heuristic inspired by Charles Darwin’s theory of natural selection
    - Reflects the process of natural selection where the fittest individuals are selected for reproduction in order to produce offspring of the next generation
  - GA in TPOT
    - TPOT will evaluate POPULATION_SIZE (number of individuals to retain in the GP population every generation) + GENERATIONS (number of iterations to run the pipeline optimization process) x OFFSPRING_SIZE (= POPULATION_SIZE by default) pipelines in total
    - With the default TPOT settings (100 generations with 100 population size), TPOT will evaluate 10,000 pipeline configurations before finishing

- Benefits
  - Automates the process of testing numerous combinations of preprocessing steps and model configurations, which can be computationally expensive and tedious to do manually
  - Capable of performing a global search and less likely to be trapped in local optimum solutions compared to other optimization methods
  - Can adapt to the specific characteristics of the data by evolving pipelines that are better suited to the problem

- Challenges
  - Computationally expensive especially for large datasets or complex problems due to the need of evaluating a large number of pipelines during the optimization process
  - Stochastic nature such that runs can be somewhat different unless the random state is fixed

- # Example AutoML implementation with TPOT

```
from tpot import TPOTClassifier
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split

# Load a sample dataset
iris = load_iris()
X, y = iris.data, iris.target

# Split the dataset into training and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)

# Initialize the TPOT classifier
tpot = TPOTClassifier(generations=5, population_size=20)

# Fit and evaluate the model
tpot.fit(X_train, y_train)
acc = tpot.score(X_test, y_test)
```

Feature Engineering

- Crucial step in the machine learning pipeline that involves transforming raw data into meaningful features that improve the performance of machine learning models
- Blend of art and science, combining statistical techniques with domain expertise to unlock the full potential of machine learning models
  - Well-engineered features can lead to simpler, more interpretable models with better performance

- Main operations
  - Feature selection
    - Identifies and retains the most relevant features
  - Feature extraction
    - Creates new features from existing ones
  - Feature transformation
    - Modifies features to better represent the data
  - Feature interaction
    - Captures relationships between features

- Handling missing values
  - Addresses gaps in data
- Encoding categorical variables
  - Converts categorical data into numerical form
- Dimensionality reduction
  - Reduces the number of features while retaining important information

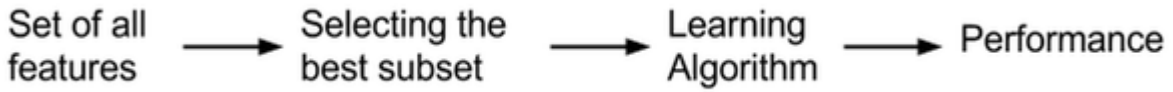
- Automated feature engineering tools
  - Feature-engine [https://feature-engine.trainindata.com/; https://github.com/feature-engine/feature_engine]
  - Featuretools [https://featuretools.alteryx.com/; https://github.com/alteryx/featuretools]
  - Scikit-learn [https://scikit-learn.org/; https://github.com/scikit-learn/scikit-learn]
  - tsfresh [https://tsfresh.readthedocs.io/; https://github.com/blue-yonder/tsfresh]
  - Feast [https://feast.dev/; https://github.com/feast-dev/feast]

Feature Selection

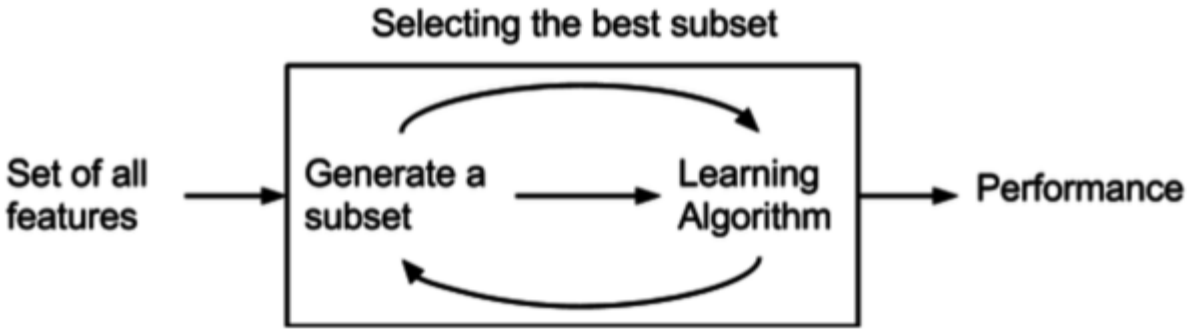
- Methods
  - Filter method
    - Ranks and selects features based on their scores or statistical measures calculated directly from the data, such as correlation, mutual information, χ^2-statistic from the χ^2 test, or *F*-statistic from the ANOVA, without involving any learning algorithm
    - May fail to capture feature dependencies and interactions

- Wrapper method
  - Iteratively adds or removes features and evaluates the performance of a model using techniques such as forward selection, backward elimination, or recursive feature elimination
  - Computationally expensive, especially for high-dimensional datasets
- Embedded method
  - Performs feature selection as part of the model construction process
  - Some machine learning algorithms like LASSO, ridge regression, and decision trees have built-in mechanisms for feature selection by assigning weights or importances to features during the training process
  - Specific to the machine learning algorithm used

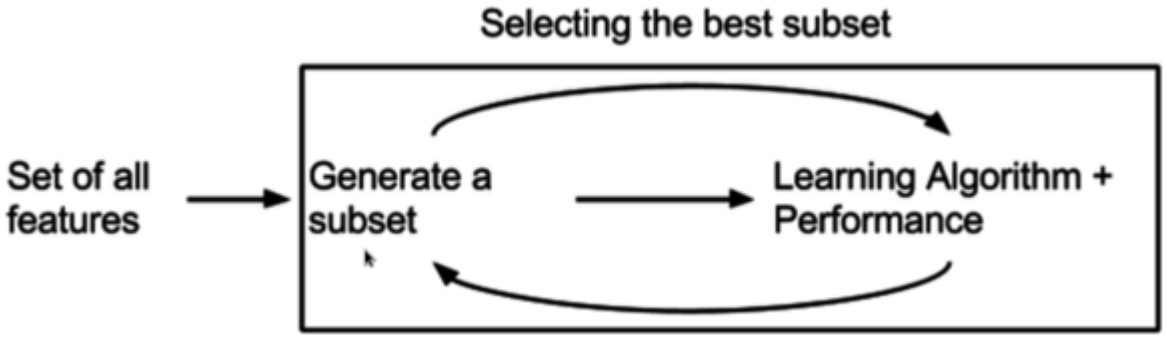
Filter method



Wrapper method



Embedded method



[https://en.wikipedia.org/wiki/Feature_selection]

Feature Selection Methods

- LASSO (Least Absolute Shrinkage and Selection Operator)
  - Regression analysis method that performs both variable selection and regularization in order to enhance the prediction accuracy and interpretability of the statistical model it produces
  - Key features
    - Regularization
      - Adds a penalty term that discourages large coefficients, which helps in shrinking some coefficients to exactly zero and thus reducing overfitting
    - Feature selection
      - Automatically selects a simpler model that only includes the most relevant features by driving some coefficients to zero
    - Interpretability
      - Induces a model that is easier to interpret because it is simpler and contains only the most important features

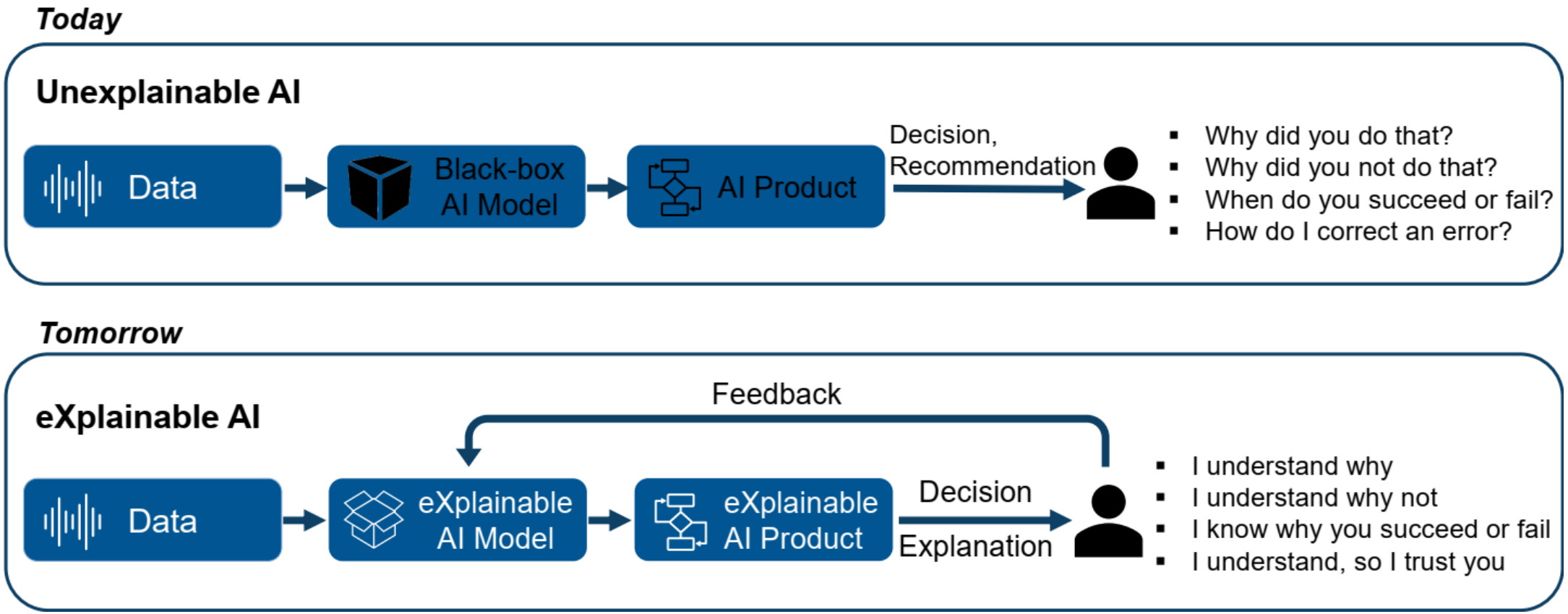
– Mathematical formulation

$$\text{Objective function} = \sum_{i=1}^{n}(y_i - \sum_{j} x_{ij}\beta_j)^2 + \lambda \sum_{j=1}^{p} |\beta_j|$$

- Shrinkage
  - As the regularization parameter (λ) increases, the coefficients are shrunk towards zero
- Selection
  - Some coefficients may become exactly zero, which means the corresponding features are effectively removed from the given model

Explainable Artificial Intelligence (XAI)

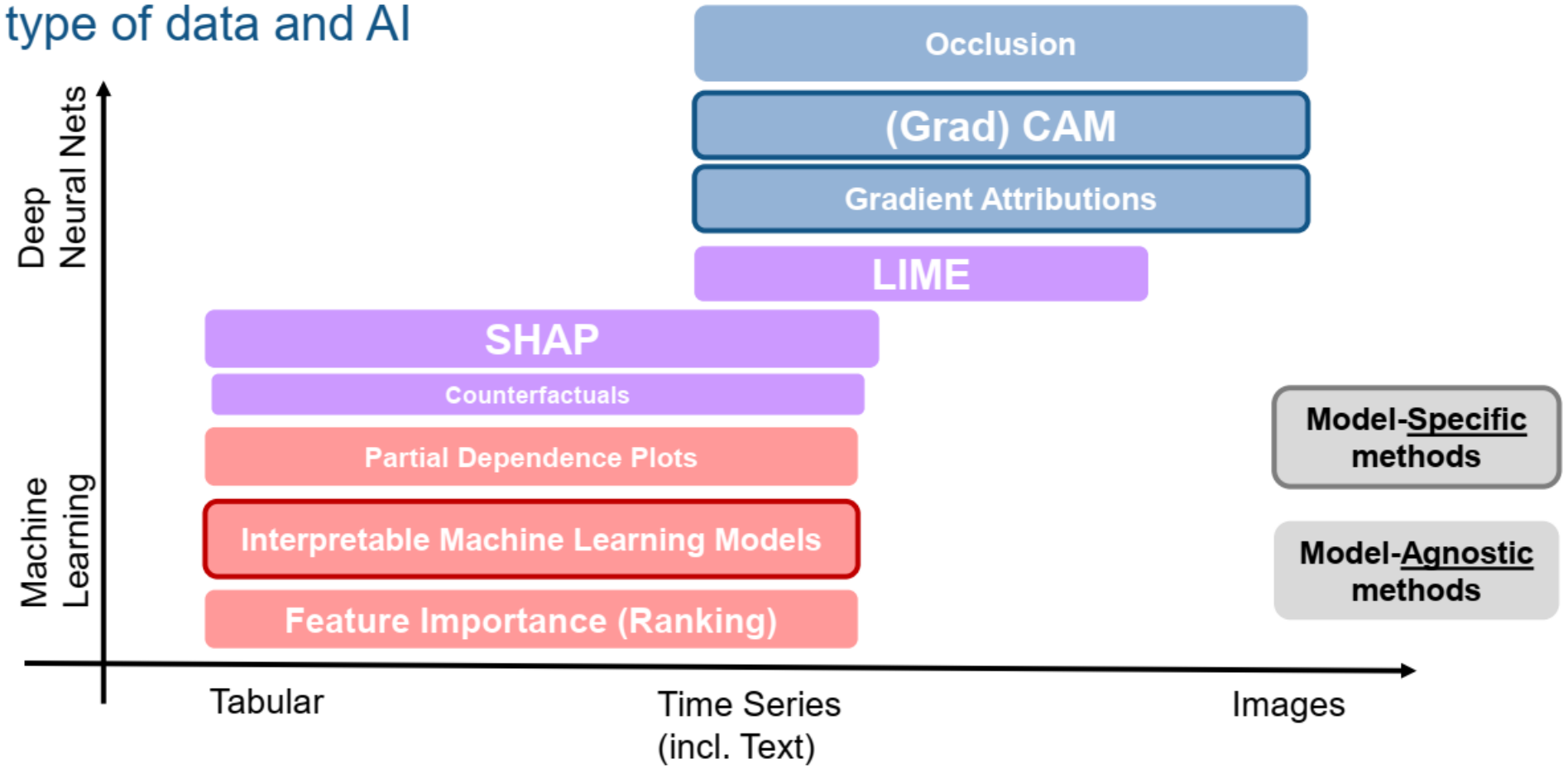
- Field that focuses on making artificial intelligence (AI) systems more interpretable, transparent, and understandable to humans
- Aims to provide explanations for the predictions made by AI models, particularly in high-stakes domains where accountability, fairness, and trust are crucial



[MathWorks Online Seminar: eXplainable AI and AI V&V]

Unexplainable vs Explainable AI

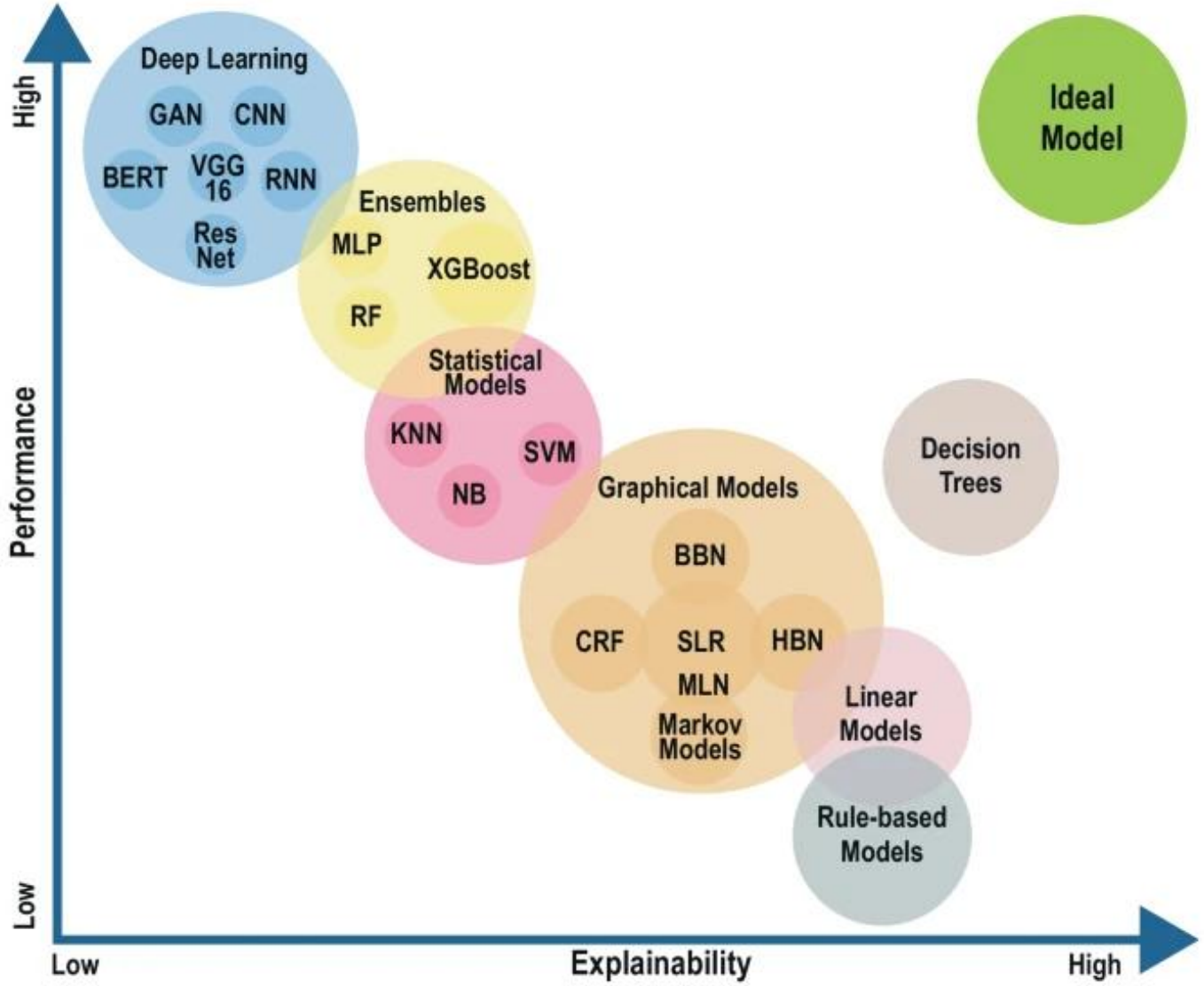
- Techniques and methods for human-understandable explanations for the behavior of AI systems
  - Feature importance and attribution
    - By identifying the most relevant features or inputs that contributed to a model's prediction
  - Model interpretability
    - By developing inherently interpretable models
  - Visual explanations
    - By highlighting the regions or features in the input data that were most influential in a model's decision-making process using visualizations



[MathWorks Online Seminar: eXplainable AI and AI V&V]

Techniques for XAI

- Challenges
  - Trade-offs between model complexity, performance, and interpretability
  - Appropriate forms and levels of explanations required for different applications and user groups



[Viswan et al., 2024]

Trade-off between Model Accuracy and Associated Explainability

SHAP (SHapley Additive exPlanations)

- Game-theoretic approach to explain the output of machine learning models
  - Particularly grounded in the Shapley value that distributes the total gain generated by the coalition of all players (features) fairly among them
- SHAP values provide a unified measure of feature importance by distributing the prediction among the features, indicating how much each feature contributes to a model's output

- Key features
  - Interpretability
    - Provides a consistent and interpretable method to understand how each feature influences model predictions
  - Additivity
    - Ensures that all feature contributions sum to the difference between actual prediction and average prediction
  - Fairness
    - Allocates feature contributions fairly by considering all possible feature combinations
  - Consistency
    - Guarantees that if a feature's contribution increases, its SHAP value also increases, maintaining consistent feature importance

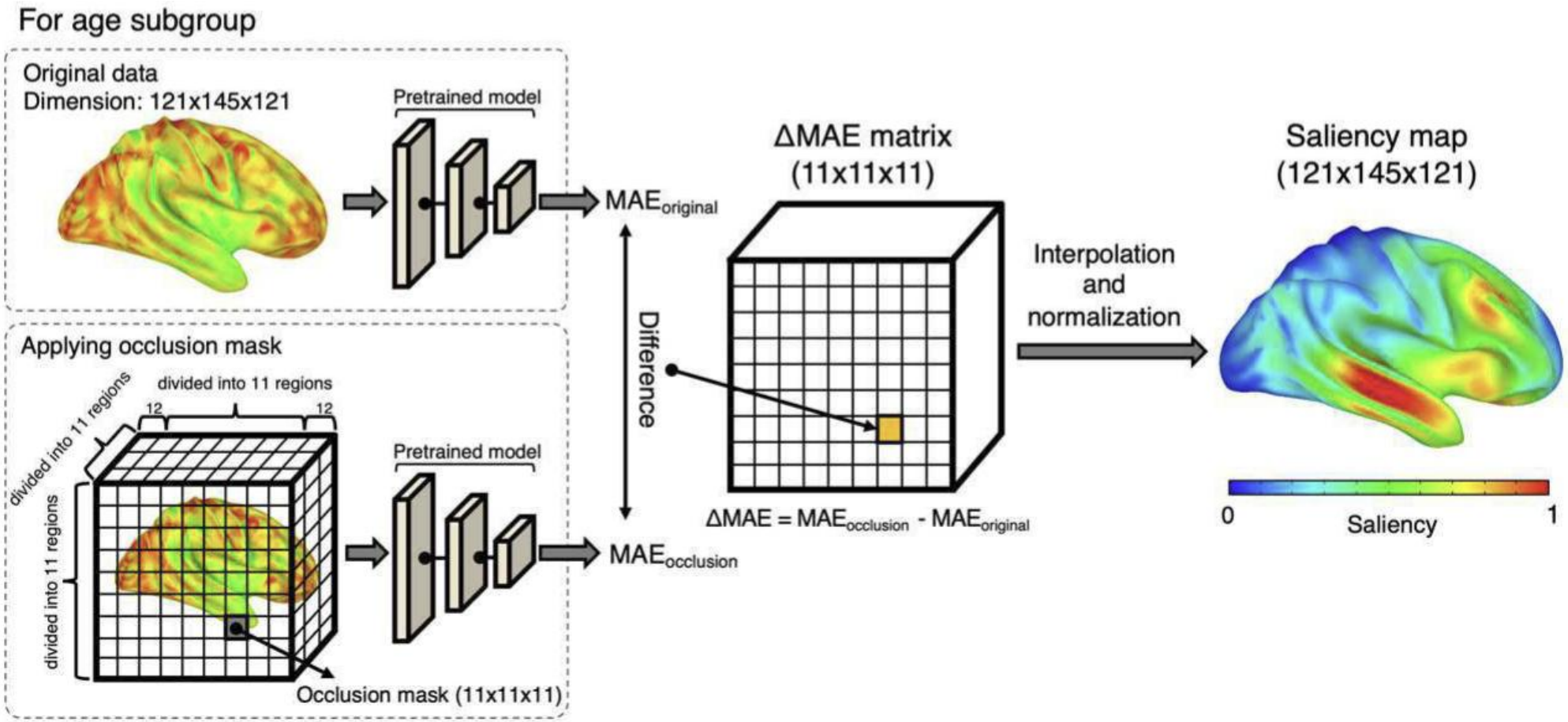
- Types of SHAP explainers
  - For any model type (model-agnostic):
    - Kernel SHAP: Universal model-agnostic approach that can explain any black-box model
    - Sampling SHAP: Approximation method based on sampling for large datasets with any model type
  - For tree-based models:
    - Tree SHAP: Optimized specifically for tree-based models
    - Partition SHAP: Effective for ensemble tree models treating them as set function models

- For deep learning models:
  - Deep SHAP: BackPropSHAP-based explainer designed specifically for neural networks
  - Gradient SHAP: Leverages gradients for efficient neural network explanations
  - GPU SHAP: Uses GPU acceleration for explaining large-scale deep learning models
- For linear models:
  - Linear SHAP: Computationally efficient explainer optimized for linear regression, logistic regression, and other linear models
- For specialized cases:
  - Exact SHAP: For models where exact Shapley values can be computed
  - Group SHAP: For explaining groups of features across any model type

Occlusion Sensitivity Analysis

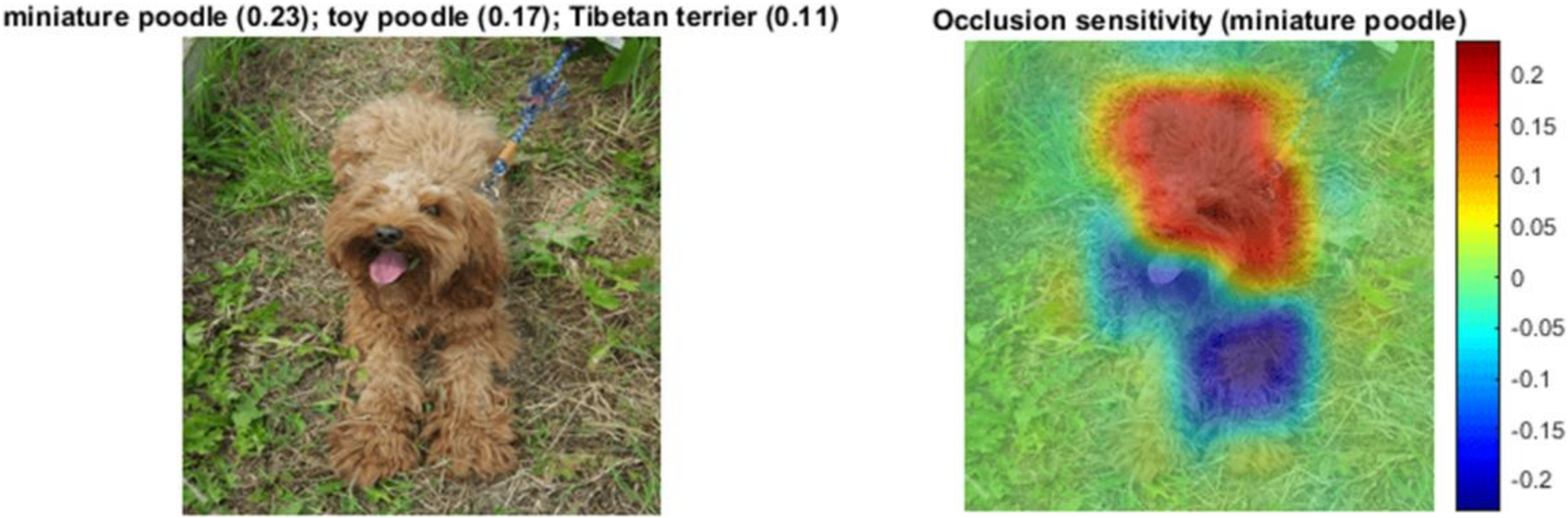
- Technique for understanding the importance of different regions in an image for a model's prediction
- Based on the idea that image regions that cause a larger change in a model's prediction when occluded are considered more important or sensitive for the task at hand
- Computationally expensive, especially for large images and models

- Occlusion sensitivity map
  - Computed by perturbing small regions of an image by replacing it with an occluding mask, typically a zero-valued mask, moving the mask across the image, and recording a change in a model's prediction for each occluded region
  - Represents a model's sensitivity to occlusion in different regions of an image
  - Highlights which parts of an image are most important to a model's prediction



[Lee et al., 2022]

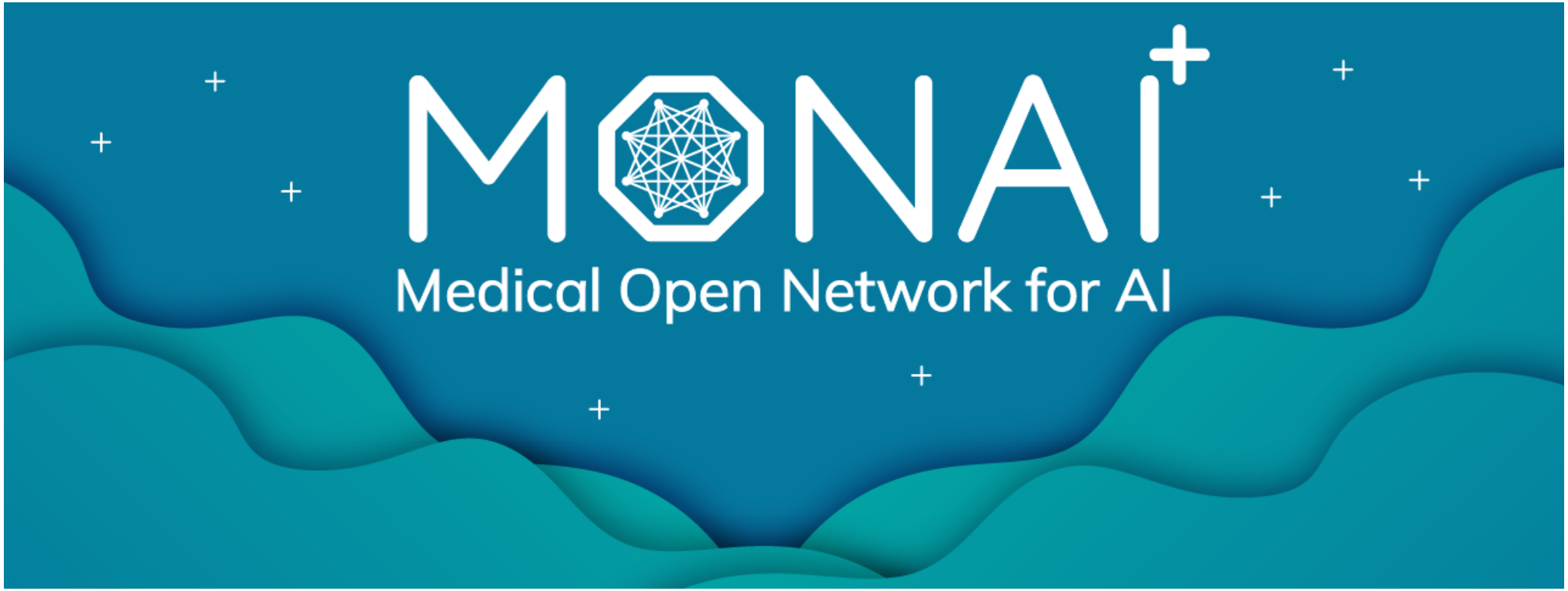
Occlusion Sensitivity Analysis for Explaining Image's Contributions



[https://www.mathworks.com/help/deeplearning/ug/understand-network-predictions-using-occlusion.html]

Occlusion Sensitivity Map Showing Image's Contributions

Medical Open Network for AI (MONAI)



[https://github.com/Project-MONAI]

- Project MONAI
  - Initiative started initially by NVIDIA and King's College London to establish an inclusive community of AI researchers to develop and exchange best practices for AI in healthcare imaging
    - Grown into a major consortium with over 25 universities, medical institutions, and industry partners
    - Established as the global standard for medical AI development
  - Aimed to define, standardize, develop, and exchange best practices for AI in healthcare by unifying the fragmented healthcare AI software field resulted from the disjointed development of several platforms

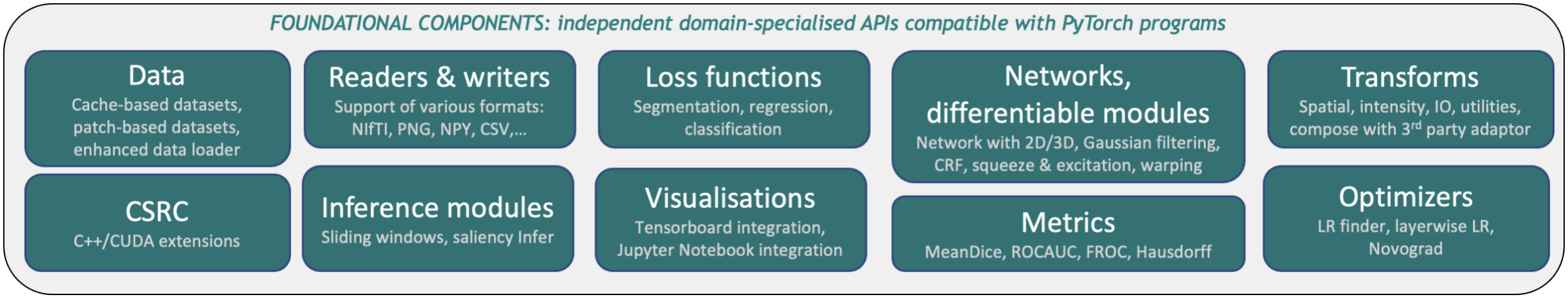
- Released multiple open-source PyTorch-based frameworks for annotating, building, training, deploying, and optimizing AI workflows in healthcare
  - MONAI Core: Enhanced framework for training AI models with expanded support for federated learning, zero/few-shot learning, and foundation model fine-tuning
  - MONAI Label: Advanced annotation platform with active learning capabilities, multi-modal annotation support, and AI-assisted labeling
  - MONAI Generative: Framework for medical image synthesis, reconstruction, and simulation using diffusion models and generative adversarial networks
  - MONAI Federated: Platform for privacy-preserving collaborative model training across institutions

- MONAI Deploy App ADK: Expanded toolkit for seamless integration of AI models into clinical workflows with FHIR/DICOM interoperability and regulatory compliance features
- MONAI Model Zoo: Comprehensive repository with 200+ pre-trained models, standardized benchmarks, and domain-specific adaptation tools

- MONAI Core
  - PyTorch-based, open-source, freely available, community-supported, and consortium-led framework (suite of libraries, tools, and SDKs) for deep learning in healthcare
    - Extends PyTorch to support medical data, with a particular focus on imaging, video, and other forms of structured data, as part of PyTorch ecosystem (tools, libraries, and more built up around the core PyTorch functionality to support, accelerate, and explore AI development)

- Provides field-specific and domain-optimized functionality that is not often supported by general-purpose frameworks such as Tensorflow and PyTorch
  - Medical images are often stored in complex formats with rich meta-information, with the data volumes being high-dimensional and requiring carefully designed manipulation procedures
  - If healthcare AI models are to be built using a general-purpose framework, significant functionality would need to be developed and tested, thus increasing the length of and the risks associated with the full research and development life-cycle
- Provides wrappers and adaptors that allow popular healthcare AI tools to be used from within MONAI
  - Developed with minimal required dependencies, namely PyTorch and NumPy

– Modules
  - **`monai.data`**: datasets, readers/writers, and synthetic data
  - **`monai.losses`**: classes defining loss functions
  - **`monai.networks`**: network definitions, component definitions, and PyTorch-specific utilities
  - **`monai.transforms`**: classes defining data transforms for pre-processing and post-processing
  - **`monai.csrc`** and **`monai.extensions`**: C++/CUDA extensions for MONAI core Python APIs
  - **`monai.visualize`**: utilities for data visualization
  - **`monai.metrics`**: metric tracking and analysis tools
  - **`monai.optimizers`**: classes defining optimizers



[Cardoso et al., 2021]

MONAI Core Modules

Model Performance Metrics

- Predicting memory performance
  - Mean absolute error (MAE)
    - (sum of absolute errors)/(sample size)
- Predicting sex
  - Accuracy
    - Proportion of correct predictions

		Predicted condition			
	Total population $= P + N$	**Positive (PP)**	**Negative (PN)**	Informedness, bookmaker informedness (BM) $= TPR + TNR - 1$	Prevalence threshold (PT) $= \frac{\sqrt{TPR \times FPR} - FPR}{TPR - FPR}$
Actual condition	**Positive (P)**	**True positive (TP),** hit	**False negative (FN),** type II error, miss, underestimation	True positive rate (TPR), recall, sensitivity (SEN), probability of detection, hit rate, power $= \frac{TP}{P} = 1 - FNR$	False negative rate (FNR), miss rate $= \frac{FN}{P} = 1 - TPR$
	Negative (N)	**False positive (FP),** type I error, false alarm, overestimation	**True negative (TN),** correct rejection	False positive rate (FPR), probability of false alarm, fall-out $= \frac{FP}{N} = 1 - TNR$	True negative rate (TNR), specificity (SPC), selectivity $= \frac{TN}{N} = 1 - FPR$
	Prevalence $= \frac{P}{P + N}$	Positive predictive value (PPV), precision $= \frac{TP}{PP} = 1 - FDR$	False omission rate (FOR) $= \frac{FN}{PN} = 1 - NPV$	Positive likelihood ratio (LR+) $= \frac{TPR}{FPR}$	Negative likelihood ratio (LR−) $= \frac{FNR}{TNR}$
	Accuracy (ACC) $= \frac{TP + TN}{P + N}$	False discovery rate (FDR) $= \frac{FP}{PP} = 1 - PPV$	Negative predictive value (NPV) $= \frac{TN}{PN}$ $= 1 - FOR$	Markedness (MK), deltaP (Δp) $= PPV + NPV - 1$	Diagnostic odds ratio (DOR) $= \frac{LR+}{LR-}$
	Balanced accuracy (BA) $= \frac{TPR + TNR}{2}$	F_1 score $= \frac{2PPV \times TPR}{PPV + TPR} = \frac{2TP}{2TP + FP + FN}$	Fowlkes–Mallows index (FM) $= \sqrt{PPV \times TPR}$	Matthews correlation coefficient (MCC) $= \sqrt{TPR \times TNR \times PPV \times NPV} - \sqrt{FNR \times FPR \times FOR \times FDR}$	Threat score (TS), critical success index (CSI), Jaccard index $= \frac{TP}{TP + FN + FP}$

[https://en.wikipedia.org/wiki/Confusion_matrix]

Accuracy in a Confusion Matrix

Score Evaluation (6 Points)

- Comprehensive AI model development strategy (2 points)
  - Data management and preprocessing
  - Model architecture design
  - Training protocol
  - Performance evaluation
  - Model validation
  - Resource management

- Effective use of multimodal MRI information (2 points)
  - Grey matter and white matter maps/features from structural MRI
  - Regional homogeneity and default mode network maps/features from resting state functional MRI
  - Fractional anisotropy and mean diffusivity maps/features from diffusion-weighted MRI
- Prediction performance of AI model on test set (2 points)
  - In predicting memory performance, MAE for 10 individuals in the test set
  - In predicting sex, accuracy for 50 individuals in the test set

- AI model explanation analysis (up to 2 bonus points available)
  - To better understand the reasoning behind a model's prediction: how much each brain area contributes to a model's prediction
  - To identify and mitigate potential biases or errors