Aero-Engines AI – A Machine-Learning App for Aircraft Engine Concepts Assessment

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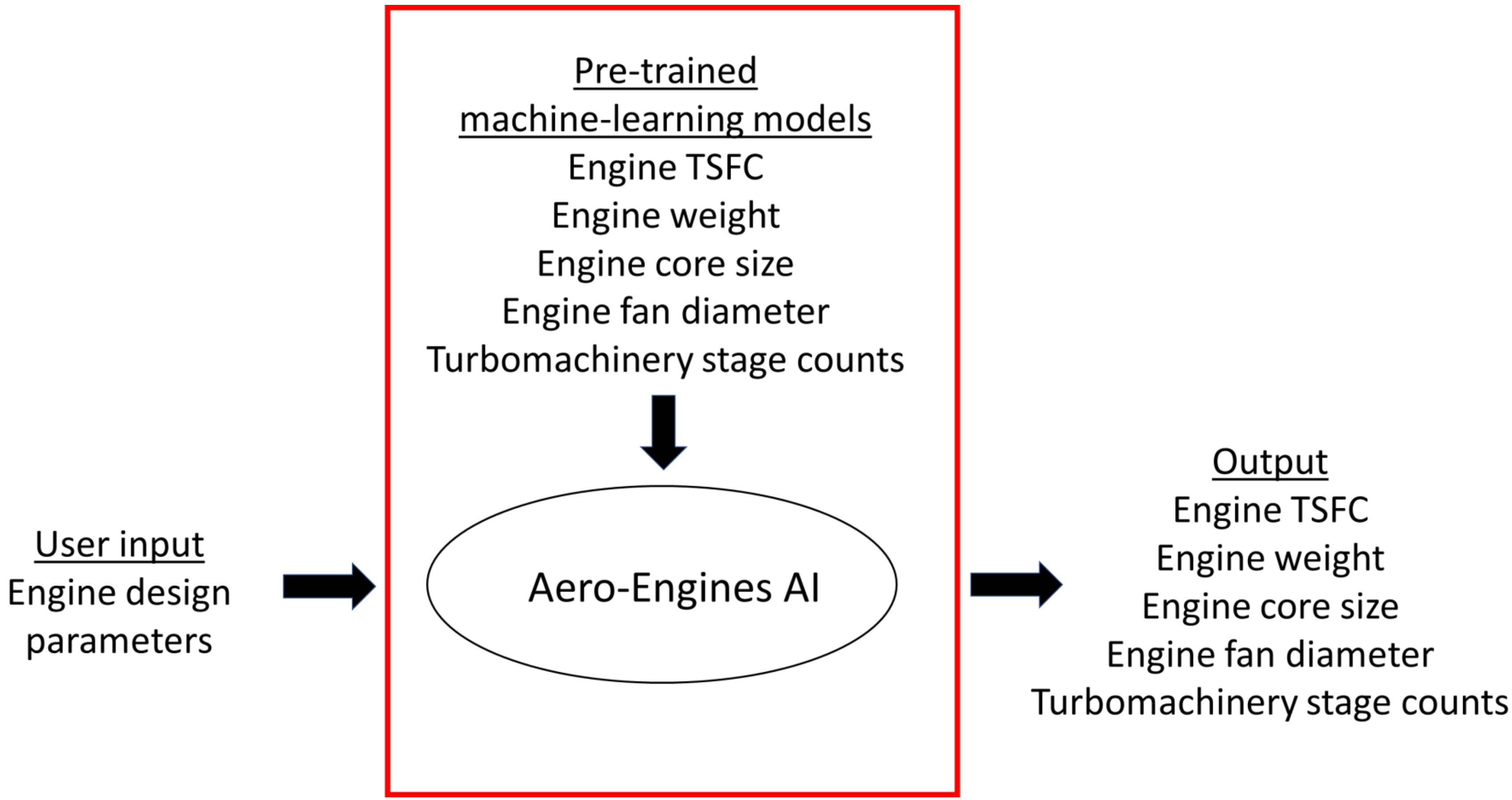
Structure of Aero-Engines AI App



Objectives/ Motivation

- To develop an engine **conceptual design tool** that would:
  - ➢ enable ***expeditious*** assessment (with reasonably good accuracy)
  - ➢ enable ***data-driven/data-informed*** decision making

Outlines

- Engine data collection, preparation, and augmentation
- Machine learning (ML) models training and cross validation
- ML models testing
- App design for ML models deployment
- Monitoring and updating

ML models development

ML models deployment

Tong, M. T., "Using Machine Learning to Predict Core Sizes of High-Efficiency Turbofan Engines," GTP-19-1338, ASME Journal of Engineering for Gas Turbines and Power, Volume 141, Issue 11, November 2019.

Tong, M. T., "Machine Learning-Based Predictive Analytics for Aircraft Engine Conceptual Design," NASA TM-20205007448, October 2020.

ML Model Training Requires Big Data

GE	CFM	P&W	Rolls Royce	IAE
CF6-6D	56-2C1	JT8D-7 certified 1966	RB211-22B	V2500-A1
CF6-80C2A1	56-3B1	JT9D-3A	RB211-524B	V2522-A5
CF6-80C2B1	56-3C1	JT9D-7	RB211-535C	V2524-A5
CF34-10A	56-5A1	2037	Trent 768	V2525-D5
CF34-3A	56-5B1	4052	Trent 553-61	V2527-A5
•	•	•	•	V2528-D5
•	•	•	•	V2530-A5
•	•	•	•	V2533-A5
90-94B	LEAP-1A35	6122A	Trent 970-84	
90-115B	LEAP-1B25	4168-1D	Trent XWB-84	
Genx-1B54	LEAP-1B27	1519G	Trent XWB-97	
Genx-1B70	LEAP-1B28	1527G	Trent 7000-72 certified 2018	

Open-source data (ICAO, Jane’s, Company websites…)

(minimizes ML model uncertainty)

NASA Looks To The Future

Subsonic Fixed Wing Project (SFW)	Environmentally Responsible Aviation Project (ERA)	Advanced Air Transport Technology Project (AATT)
SA-FPR1.3-GR-HW-2E	Large-DD-2014	N+3
SA-FPR1.4-GR-HW-2E	Large-DD-2015	N3CC-2016
SA-FPR1.5-DD-2D	Large-DD-2015-HWB	N3CC-2017
SA-FPR1.6-DD-2D	Large-Geared-2015	N3CC-2018
SA-FPR1.7-DD-2D	Large-Geared-2015-HWB	Small-Core-Geared
•	•	
•	•	
•	•	
SA-FPR1.3-GR-HW-2D	Medium-Geared-2014	
SA-FPR1.4-GR-HW-2D	Medium-Geared-2015	
SA-FPR1.5-GR-HW-2D	Small-DD-2015	
SA-FPR1.6-GR-HW-2D	Small-Geared-2015	

Combined Database with Data Augmentation

Engine	No. of engines
Commercial	290
NASA	122

<u>Data augmentation - example</u>

BPR	OPR	SLS Thrust (lbs)	Mach	Alt. (ft)	TSFC (lb/hr/lb)	Weight (lbs)
8.44	38.37	79377	0.85	35000	.5526	18949
8.44	38.37	87315	0.85	35000	.5526	20844

ML Models Development Approach

- Data Science
  - Dataset preparation
  - Training, cross-validation, and testing datasets

- ML algorithms:
  - Deep Learning Network (DNN) – TSFC, weight, fan diameter
  - Support Vector Machine (SVM) – core size
  - K-nearest neighbors (KNN) – turbomachinery stage counts

- Implementation:

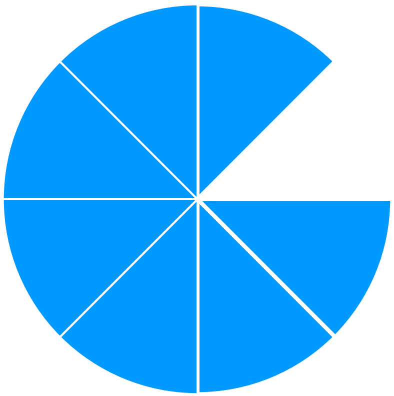
  Python and Google AI libraries
  - Keras provides building blocks for DNN
  - TensorFlow backend (computes tensors, derivatives, optimization)

Keras – Python Neural Network API

TensorFlow – Google AI library

ML Models Development - Data Science

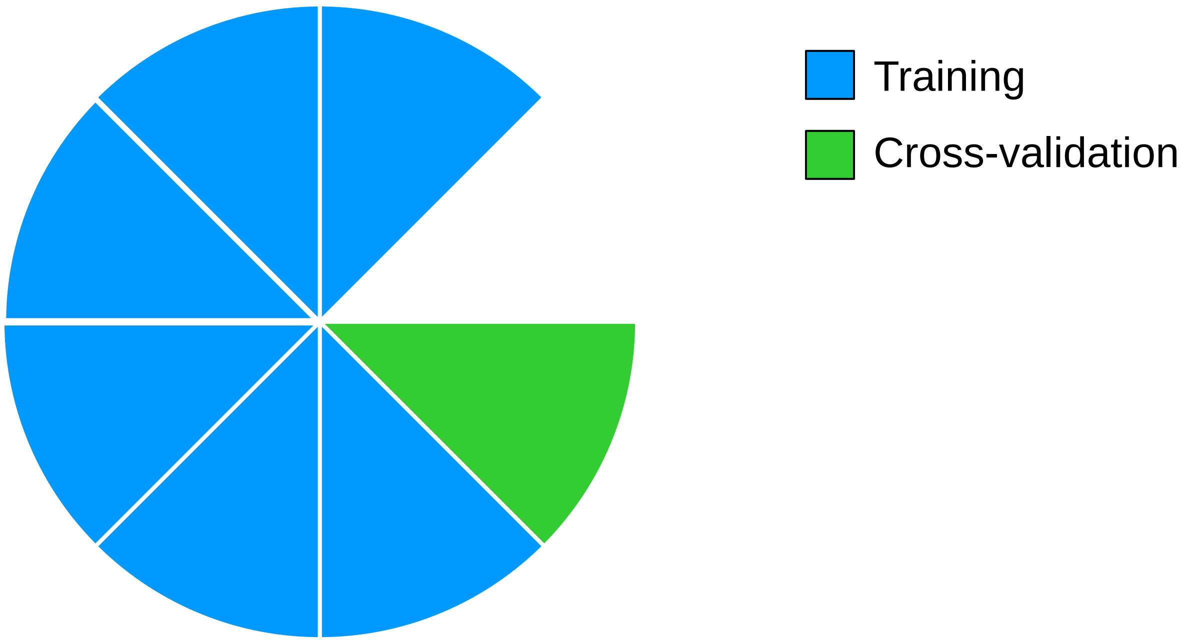
- Dataset preparation
  - shuffled (randomized), normalized, and stratified the data
  - splitted into training and testing dataset



Training dataset

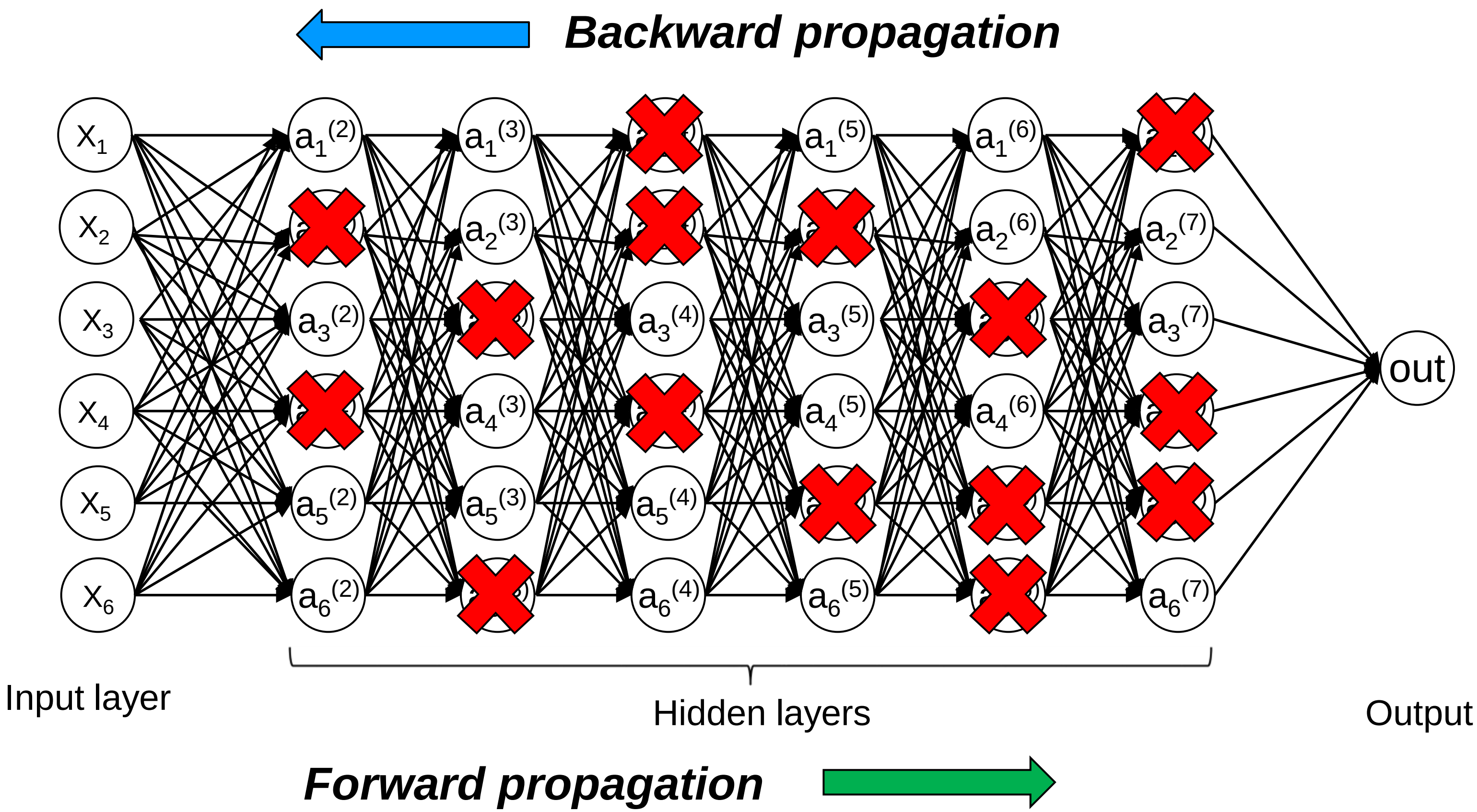
ML Models Development - Data Science

- Preliminary training and 7-fold cross-validation of the classifiers
  - adjusting/tuning hyperparameters



Important to quantify uncertainty

Deep Learning Neural Network



$a_i^{(k)}$ = activation of unit i in layer $\boxed{k = g(\sum\sum\sum w_{ij}^{(k)} x_i)}$

$w^{(k)}$ = matrix of weights controlling function from layer *k to k+1*

g = activation function (a scaled exponential linear unit function)

Training and Cross-Validation Results

Metrics	Accuracy (mean)	Uncertainty 2 standard deviations (95% confidence interval)
TSFC	98%	4%
Weight	95%	5%
Fan dia.	98%	4%
Core size	98%	5%
LPC stg. count	98%	14% (or 1 stage)
HPC stg. count	98%	8% (or 1 stage)
HPT stg. Count	96%	39% (or 1 stage)
LPT stg. Count	98%	18% (or 1 stage)
IPT stg. count	90%	44% (or 1 stage)

Cruise TSFC ML Model
Predicted Results vs. Testing Dataset

		Cruise TSFC		Accuracy			Cruise TSFC		Accuracy
Org.	Engine model	Data	Prediction	%	Org.	Engine model	Data	Prediction	%
P&W	4056	0.560			NASA ERA	Large-Geared-2015-HWB-V2	0.464		
CFM	56-5A5	0.596			GE	CF6-80C2A3	0.576		
GE	CF6-80E1A1	0.562			NASA ERA	Small-Geared-2015	0.485		
GE	CF6-80E1A3	0.562			NASA SFW	Simulated GE90-110B	0.549		
Rolls Royce	Trent 1000-A	0.506			GE	CF34-3A	0.704		
CFM	LEAP-1A35	0.536			P&W	1519G	0.544		
Rolls Royce	Trent 890-17	0.560			GE	CF6-80C2B2	0.576		
GE	90-94B	0.545			P&W	JT9D-20	0.624		
Rolls Royce	BR715-A1-30	0.620			P&W	JT8D-17R	0.825		
P&W	4074	0.560			P&W	4060	0.560		
GE	CF6-6D	0.646			P&W	4460	0.560		
NASA SFW	SA-FPR1.5-GR-HW-2E	0.515			NASA ERA	Large-Geared-2014	0.458		
NASA SFW	SA-FPR1.3-GR-HW-2D	0.470			CFM	CFM56-5B1	0.600		
P&W	JT9D-7Q	0.631			P&W	2040	0.563		
NASA ERA	Small-Geared-2014	0.486			GE	CF6-50C1	0.657		
GE	CF34-8C1	0.664			P&W	JT9D-7J	0.631		
CFM	56-5A4	0.596			NASA SFW	SA-FPR1.5-GR-HW-2D	0.502		
P&W	4090	0.560			P&W	2037	0.563		
P&W	JT9D-7A	0.625			GE	90-76B	0.545		
Rolls Royce	BR715-C1-30	0.620			NASA SFW	SA-FPR1.4-DD-2D	0.479		
NASA ERA	Small-DD-2015-V2	0.524			Rolls-Royce	Trent 875	0.560		
P&W	JT9D-7R4H1	0.628			CFM	56-2C1	0.651		
GE	GEnx-1B64	0.514			GE	CF6-50C	0.657		

Average accuracy = 98.3%

Lowest accuracy = 94.8%

App Design for ML Models Deployment

- Created using *Tkinter*, a Python GUI.
- Converted to a MS Windows executable using ***pyinstaller*** (Python library)
  - ➢ reduce complexity
  - ➢ easy access (without the need of Python installed)
- Focused on user experience
  - ➢ simple, intuitive, ease of use (hard work done behind the scene)
  - ➢ effective & efficient usability (instruction manual not required)

A demo of the App

Monitoring and Updating

- Keep track of and update engine database as needed:
  - Commercial engines – add data to the database if new engine data become available (e.g., Rolls Royce UltraFan, EIS 2030?)
  - NASA's engine data are R&D in nature and could change over time

To ensure optimal performance of ML models

Summary

- First version Aero-Engines AI app developed for turbofan conceptual assessment
- The app enables **expeditious** turbofan conceptual assessment
- The app enables **data-driven/data-informed** decision making
- Need more data to improve accuracy/reduce uncertainties
- Limited availability of open-source data is a challenge to overcome

What's next?

- Develop ML models for electric machines:
  - to enable hybrid-electric turbofan assessment

- Develop detailed ML models at the engine component level:
  - to characterize impacts of T4, efficiencies, turbine/compressor loadings, turbine cooling, ………

- Develop ML models for turboshaft engine

- Develop ML models at the aircraft level (tube-and-wing, BWB, rotocraft, …
  - fuel burn, emissions, takeoff field length, ……

One common challenge – limited availability of open-source data

Acknowledgement

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Data are digital gold!

Backup Slides

Features for Engine Weight ML Model development

BPR
OPR
SLS thrust
Fan diameter
Drive system (direct-drive or geared)
System configuration (2-shaft or 3-shaft)
Engine timeframe (a technology indicator)

Cruise TSFC Prediction

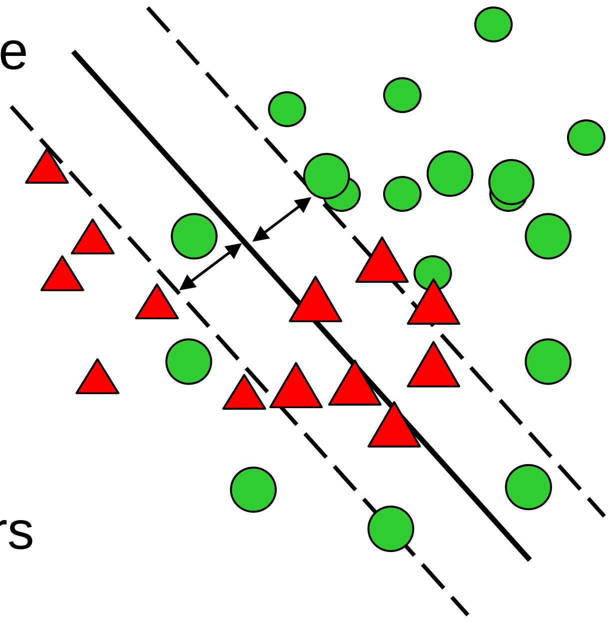
Input parameters	Data available
Thrust	Thrust @ SLS
OPR	OPR @ SLS
FPR	BPR @ SLS
Cruise Mach	Cruise Mach
Cruise altitude	Cruise altitude
Fan, LPC, HPC effs.	?
LPT, HPT effs.	?
Turbine cooling flow	?
T4	?

- Highly dependent on engine technologies
- “Engine Certified Year” – a good indicator of engine tech. level

Algorithm
ML Models for Engine Core Sizes

Support Vector Machine (SVM)

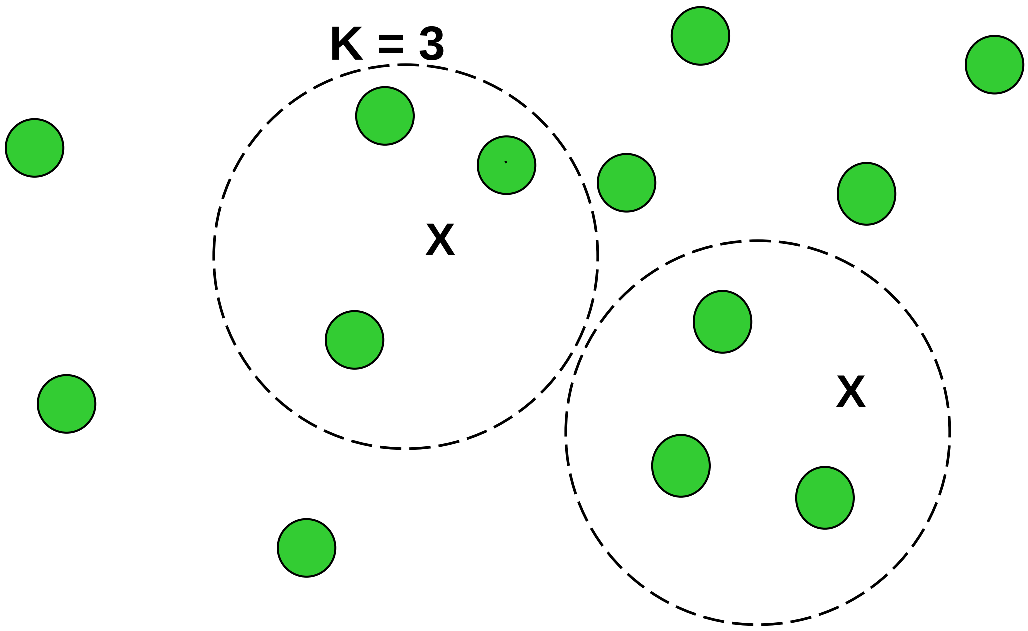
- Identifies an optimal hyperplane that maximizes the separation margin between the two classes
- Uses kernel function for nonlinearly-separated classes
- Training involves minimization of the cost (error) function
- Training involves adjusting/tuning hyperparameters
  - penalty parameter
  - parameter that controls the tradeoff between error and separation margin



Ref: : Geron, A., "Hands-On Machine Learning with Scikit-Learn and TensorFlow," first edition, March 2017. Published by O'Reilly Media, Inc.

Algorithm
ML Models for Turbomachinery Stage Counts

K-Nearest Neighbors (KNN)



Ref: : Geron, A., “Hands-On Machine Learning with Scikit-Learn and TensorFlow,” first edition, March 2017. Published by O’Reilly Media, Inc.