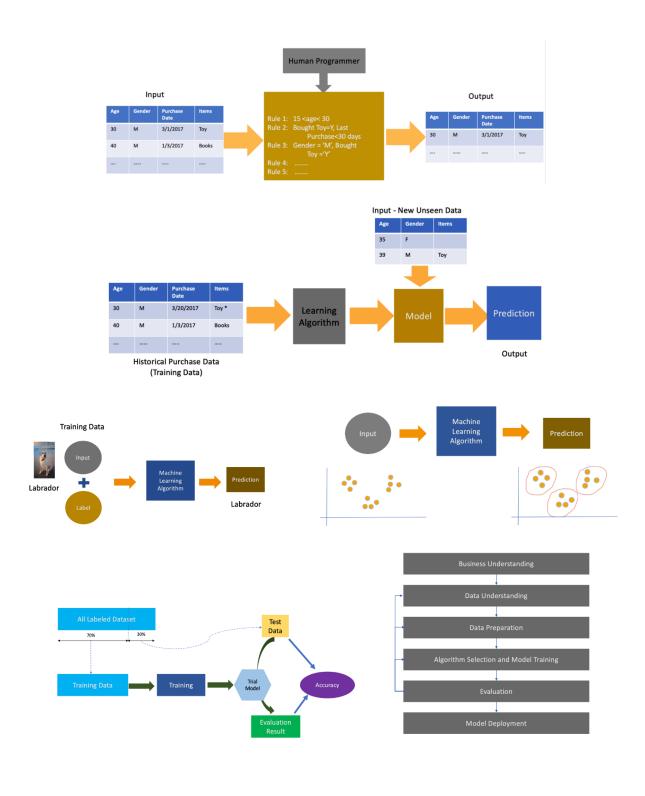
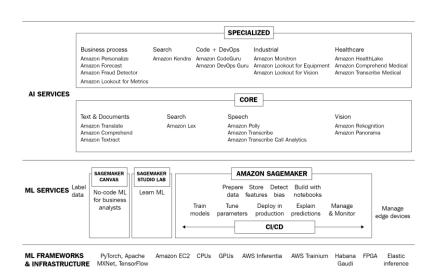
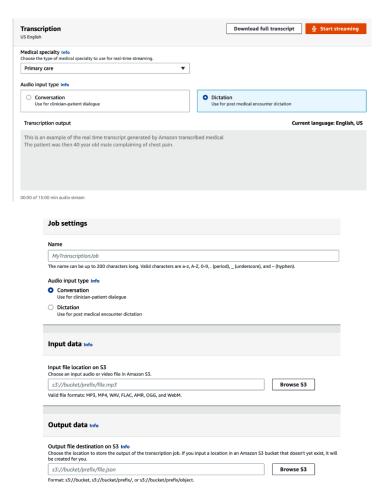
Chapter 1: Introducing Machine Learning and the AWS Machine Learning Stack



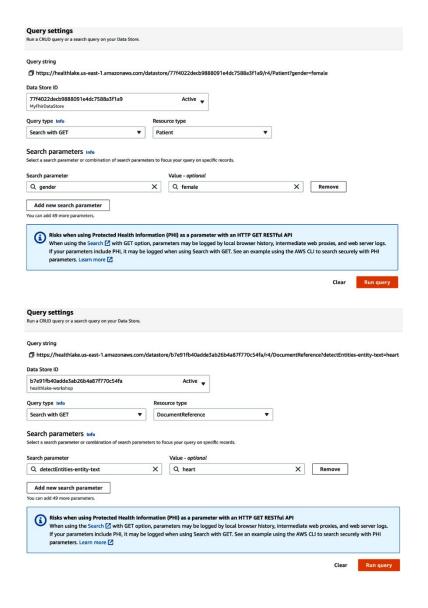


Chapter 2: Exploring Key AWS Machine Learning Services for Healthcare and Life Sciences

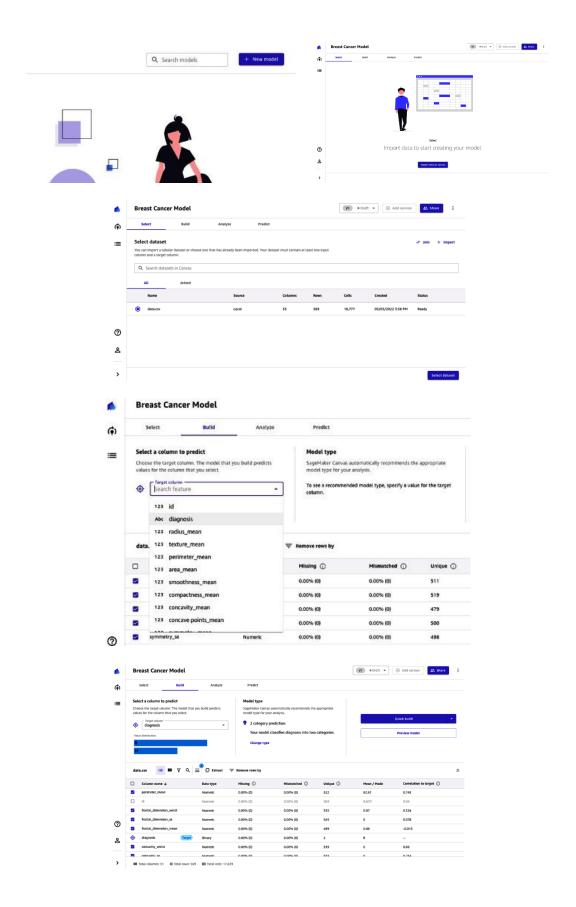


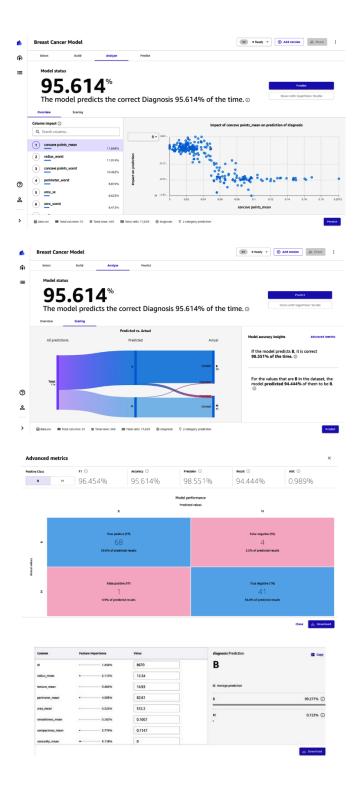
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Name						
MyVocabulary01						
The name can be up to 200 i	haracters long. Valid charact	ers are a-z, A-Z, and 0-9.				
Vocabulary input file loc Browse, type or paste the UF	ation in Amazon S3 Info L of your input vocabulary fi	le in S3.				
s3://MyBucketName/V	ocabularyFileName				Browse S3	
File format: txt, maximum si	e 50 KB. Table format only.					
Tags - optional A tag is a label you can add to No tags associated with		help you organize, search, or	filter your data. Each tag consists of a ke	y and an	optional value, in the form 'key	/:value'.



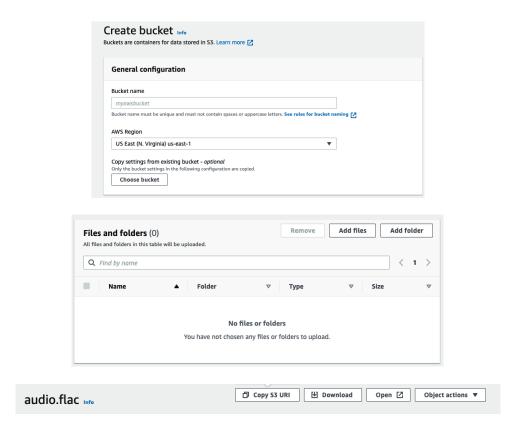


Chapter 3: Machine Learning for Patient Risk Stratification

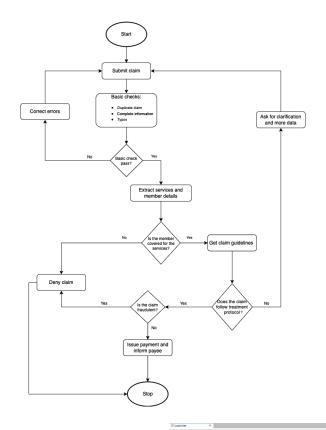


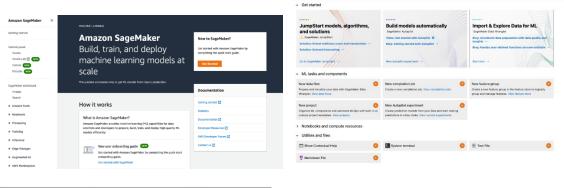


Chapter 4: Using Machine Learning to Improve Operational Efficiency for Healthcare Providers



Chapter 5: Implementing Machine Learning for Healthcare Payors



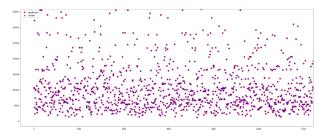


								Data types - Tran	sform: 2008_BSA	_Inpatient_Claims_I	PUF.csv						
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						Previous Disp	playing 1 - 3 Next	Step 2. Data types						Expert data	TRANSF		
								P_CLM_ID (string)	BENE_SEX_IDENT	BENE_AGE_CAT_CO	IP_CLM_BASE_DRG	IP_CLM_ICSR_PRCS	P_CLM_DAYS_CD (-	P_DRG_QUINT_F	+ Iddistra		
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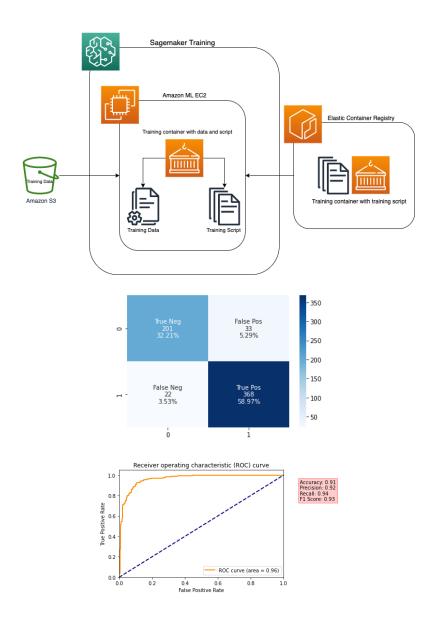




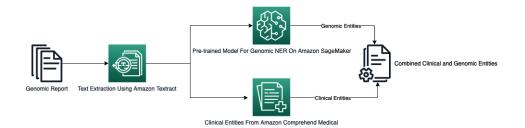




Chapter 6: Implementing Machine Learning for Medical Devices and Radiology Images



Chapter 7: Applying Machine Learning to Genomics



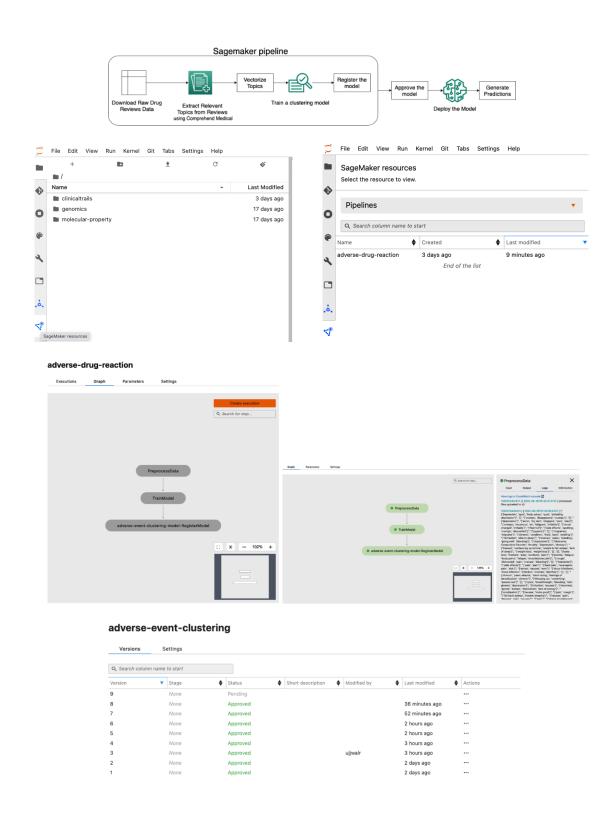
Chapter 8: Applying Machine Learning to Molecular Data

! ls models/

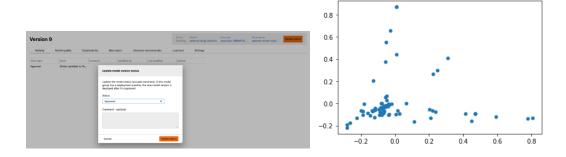
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cyp3a4_substrate_carbonmangels_model cyp3a4_veith_model half_life_obach_model hia_hou_model hydrationfreeenergy_freesolv_model lipophilicity_astrazeneca_model pgp_broccatelli_model solubility_aqsoldb_model

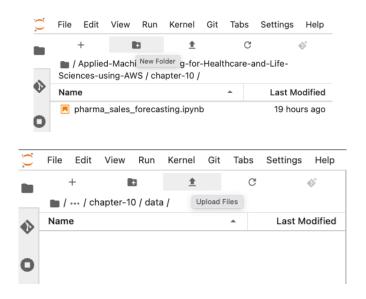
Chapter 9: Applying Machine Learning to Clinical Trials and Pharmacovigilance



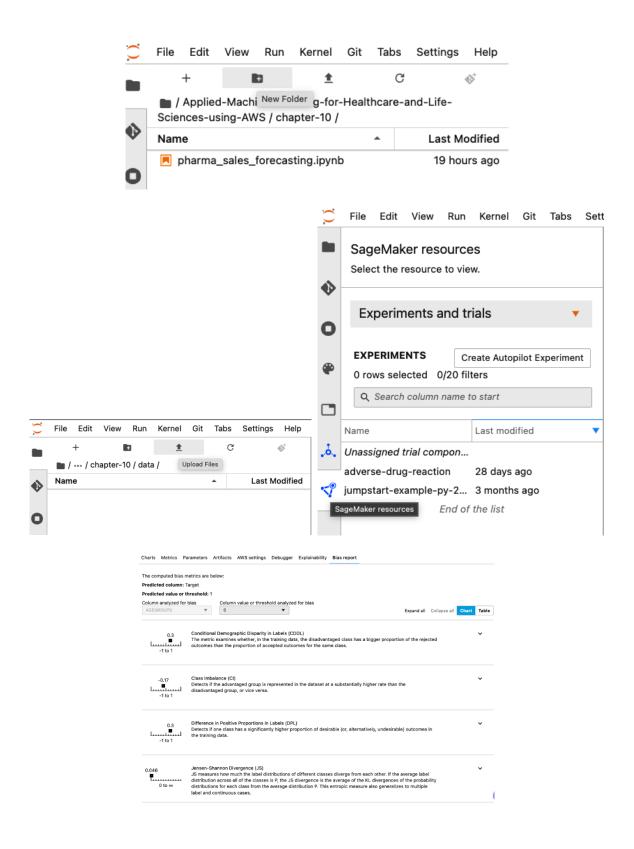




Chapter 10: Utilizing Machine Learning in the Pharmaceutical Supply Chain



Chapter 11: Understanding Common Industry Challenges and Solutions



The computed bias metrics are below:

Predicted column: Target

Predicted value or threshold: 1

Column analyzed for bias

AGEGROUPS

Column value or threshold analyzed for bias

1

Expand all Collapse all Chart Table

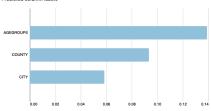
Bias metric	Bias value	Description
Conditional Demographic Disparity in Labels (CDDL)	-0.023	The metric examines whether, in the training data, the disa
Class Imbalance (CI)	0.97	Detects if the advantaged group is represented in the data
Difference in Positive Proportions in Labels (DPL)	-0.54	Detects if one class has a significantly higher proportion of
Jensen-Shannon Divergence (JS)	0.052	JS measures how much the label distributions of different
Kullback-Liebler Divergence (KL)	-0.36	In a binary case, a relative entropy measure of how much t
Kolmogorov-Smirnov Distance (KS)	0.54	This metric is equal to the maximum divergence in a label a
L-p Norm (LP)	0.54	This measure of distance in label distributions is the norme
Total Variation Distance (TVD)	0.27	This measure of distance in label distributions is half the H
Accuracy Difference (AD)	-0.37	This metric examines whether the classification by the mod
Conditional Demographic Disparity in Predicted Labels (CD	-0.069	The metric examines whether the model predicted a bigger
Difference in Acceptance Rates (DAR)	-0.051	The difference in the rates of positive predicted outcomes
Difference in Conditional Acceptance (DCA)	3.6	This metric compares the actual labels to the predicted lab
Difference in Conditional Outcomes (DCR)	-0.6	This metric compares the actual labels to the predicted lab
Disparate (Adverse) Impact (DI)	10	This metric examines whether the model predicts outcome
Difference in Positive Proportions in Predicted Labels (DPPL)	-0.9	This metric examines whether the model predicts outcome
Difference in Rejection Rates (DRR)	-0.6	The difference in the rates of negative predicted outcomes
Counterfactuals: Fliptest (FT)	1	The fliptest is an approach that looks at each member of th
Recall Difference (RD)	-0.79	Checks whether there is a difference in recall of the model \dots
Treatment Equality (TE)	-71	This is defined as the difference in the ratio of false negativ

Charts Metrics Parameters Artifacts AWS settings Debugger Explainability Bias report

Explaining your model's predictions

Amazon SageMaker Studio helps you understand your machine learning model by portraying the importance of its features in terms of SHAP values. We plot the aggregated SHAP value for each feature across all instances of the dataset.

Predicted column: label0



Export PDF report Download raw data