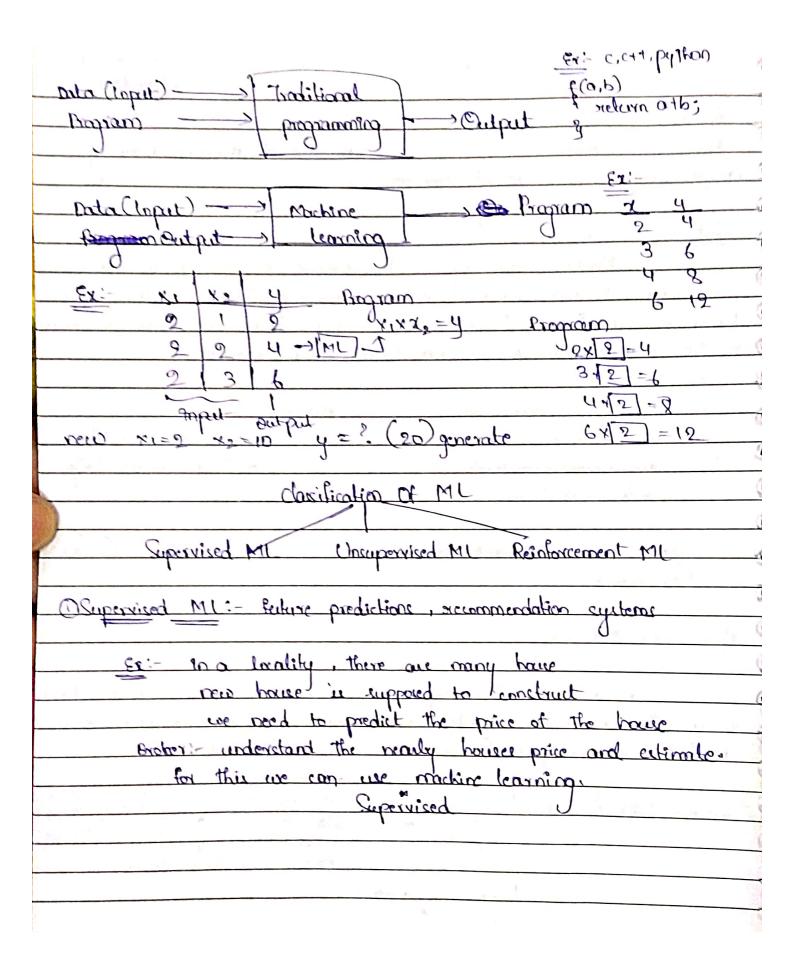
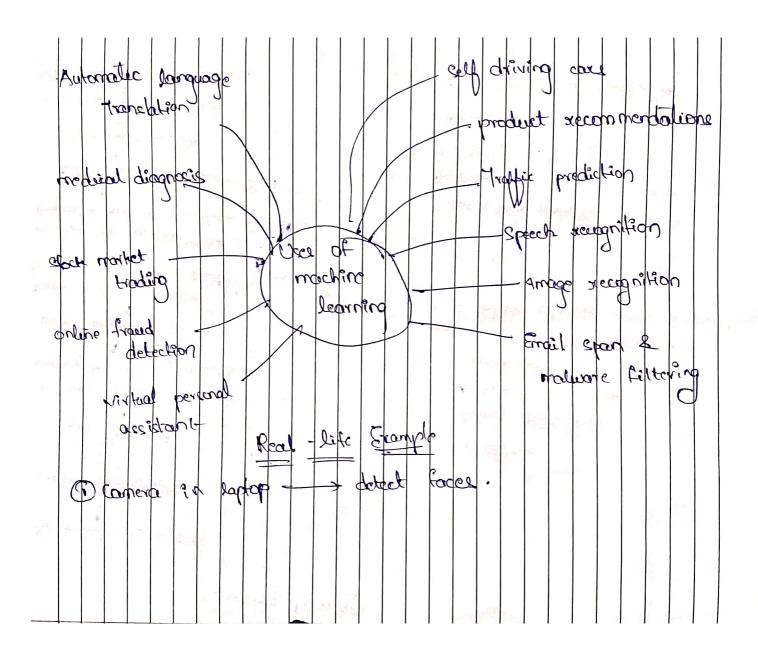
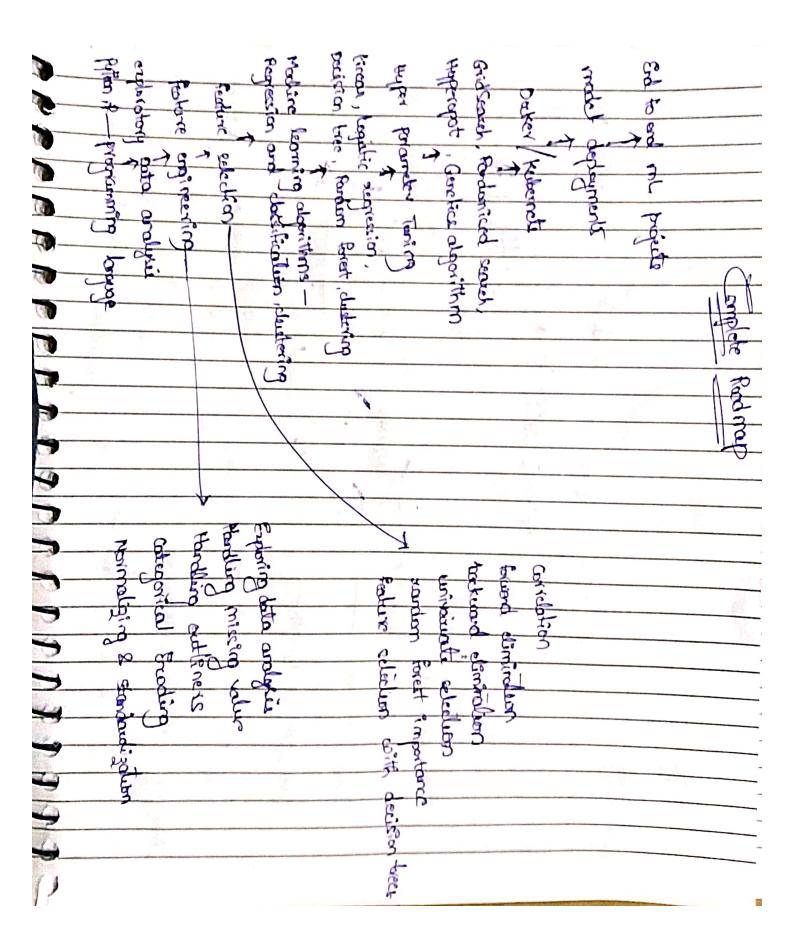
| We Carlo - Mr Borl -1 10:00 Am                                     |
|--|
| Youlube -> Planlist 19-04-2025                                     |
| Moil - span Because of machine learning                            |
| Amoun Shopping - Bought together                                   |
| Total Indian   |
| what is machine learning?  |
| Machine tearning is the science of getting computers to            |
| Lean and act like humane do, and improve their learning over       |
| time in autoroman fashion, by feeding Them data and informate      |
| In the form of observations and send-world interactions            |
| Eri  |
| without making learning making learning                            |
| yatube paylist at creates paylist on ette                          |
| or create our and pure without human help.                         |
| and store them.  |
|  |
| flipkart iden you senish for bod sheets in bought together you get |
| (a) ped conex.   |
|  |
| Hay does MI work?  |
|  |
| a machine learning system learns from historical data              |
| build the prediction models and coherever it receives new data     |
| predict the output for it.   |
|  |
| Input part data Fraining Machine Reilding Dutput                   |
| toming toursel   |
| agaithin model   |
|  |
| reco dota  |
|  |



| Unsupervised Machine Learning: - dossification tack  |
|--|
| t = Committee - constitution tack  |
| Est = D wh with  |
| Bucket with lots of fruits of different types.   |
| Rased on appearence was divide them and have   |
| ceperately like Arde   |
| Ex:- Bucket with lote of fruits of different types.  Brused on appearence you divide them and keep separately like Apples, margoes, harman at an pine  |
| rature of data and divide them into groups.  |
| rature of data and divide the al   |
| arrive them toto draibs.   |
| 11 and the same of |
| Unsupervised teaming is all about graupism.  |
|  |
| Reinforcement learning: Day to Day life  |
|  |
| Ez:- game (chece) => computer ve you  Based on your movement game movement gets changed.   |
| English (control of computer ve you  |
| travel on your invenent garre movement gets  |
|  |
| automatic game pay.  |
|  |
| Advantages Of Making Centraling:   |
|  |
|  |
| Dénsity identifies trends and potterns.  (1) No human intervention needed (automation)   |
| (2) No human intervention needed (automotion)  |
| (3) Continual Improvement  |
| (4) Hardling multi-dimensional and multi-variety data.   |
| (5) Wide applications  |
| (1) Mille appropria  |
|  |
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| Dischartages of machine learning:  |          |
|--|----------|
|  | 200      |
| Data Agrisition  |          |
| 1) Time and Recources  |          |
| 3 Anterpretation of results  | <b>=</b> |
| They made susceptibility.  |          |
| the state of the s |          |
| Ezi- cell driving core   |          |
| Data Acquisition - Needs loss of and data from diff  |          |
| weather, traffic and briations.  | 1        |
| Time and Resources Training model takes exectes on   | 7        |
| and meive storage  |          |
| @ 9 Anterpretation of results - Hard to certain why the can  |          |
| made a spécufic décision ?, 1  | _        |
| (i) High e-ror susceptibility — a small sensor glitch or xare  | 7        |
| and scenario can lead to   |          |
| critical mistakes.   |          |
| a central glitch - comerce briefly stops working   |          |
| UDAR gives many distance reading   |          |
| - your misdeteets and alice  | 2        |
| even small errore like this con course the   |          |
| The corard move like broking entherly or missing a pedestrian.   | -        |
| o Rieman.  |          |
| man and the second of the seco | -        |
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|  | 3        |
|  |          |





| Programming language - Python, R  |
|---|
| R is still great for statistics. Data visualization, research but python wine when it comes to production - ready machine learning and Al applications. |
| Exploratory data analysis   |
| potential problems — before building any models.  |
| that book at your ingredients understand has fresh they are,  and what quantifies are available.  |
| EDA is like that - understanding your dataset before.   |
| EDA helps you.  Geleat the right feature for modeling   |
| · Identify patterns that can help in feature engineering chance the night model (eg: organization)  |
|   |
|   |

| Feature Engineering:   |
|--|
| Transación van data son mencional sont fenteures   |
| the trace that the trace that  |
| that help your model learn better and make accurate productions  |
| Part could are relat   |
| Real-world erample:  |
| - model that predicte it a patient bout certain disease based on   |
| - 3 pout data like:  |
| - The third this   |
| - Name DOB Weight (kg) Height (cm)   |
| - Royi 1995-08-22 to 140   |
| - a secretary to the secretary and the secretary |
| - Row data - not immediately useful  |
| - we need to extract useful of features from this.   |
|  |
| After frature orgineering -  |
| Me-28 JBMI - 95.95   |
| = weight   |
| Cheight a mrs  |
| were enjureered tealures are more welder to se   |
| to learn potterns and make accounts predictions.   |
| fricana.   |
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| La compressa de la compressa d |
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| fenture Selection:   |
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|  |
| fenture selection is the process of changing the most  |
| important igual features (columns) that contribute () the most to  |
| predicting the taxget variables.   |
| metaditi ite (arge) vaxanses.  |
| feature Engineering le Feature Scherlier   |
| Ocreate new from oxiding chance bed from existing  |
| @ raw data = Ukefulk data Removes irrelevant / redundant do  |
| 3) Add new idums semanes unnecessary idums.  |
|  |
| Hyper Paxameter Tuning:  |
|  |
| Hyper paxameters are the cellings you give before  |
| training a model and turing means finding best values tox  |
| them I to get the highest bucuxacy.  |
| and the same of th |
| Ez: Training a decision tree:  |
| un don't just gay train a model  |
| you don't just say train a model,  |
| -That's a hyper parameter.   |
|  |
| Some common hyper parameters:  |
| · mor depth - tree grows.  |
| Scarning rate -> gradient basting, remaindents   |
| on estimators -) no of trees to use.   |
| K- for KNN   |
|  |
|  |
|  |

| Darker, kubernete - model to stone   |
|--|
| Librat Charita as barically  |
| What libraries we basically Use in ML?   |
|  |
| (c) pumpy -> numerical problems, mathematical problems.  |
| - Saprio data aralysis, graphical format.  |
| 3 scikit learn -> MI model   |
| SciPy - condante and functions (like scientific mathematical   |
| condants, ea speed of light) That often  |
| (3) Tensorbow -> need in scientific / trebnical computations   |
| TO TO TO TO  |
| is basically used when upon count to early on more advanced  |
| THE PARTY OF THE P |
| hardle well and that's color was elist traditional me can't  |
| and you mile towards deep learning.  |
| For configor with the last   |
| took you'll need is the Tenerillan library - it helps you  |
| build and train deep leaving madel. I helps you  |
|  |
| Mote: 91 vire data tert /image format, upo need a addition   |
| · NUTK (Natural largerage Tookit): 1964 6  |
| Tibraries  NITK (Natural language Todkit): Used by lest processing Clike understanding and manipulating human language)  |
| · OpenCV - Veed for image processing:  |
|  |
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