Final Assignment
KB Renting Platform

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KB is a platform that connects landlord and tenants

KB is a start-up that is isrupting the home **rental market**

It offers an end-to-end **digital solution** to connect tenants and landlords

It reduces the average time needed to rent a property: from one month to **three days!**

This is thanks to:

- fast visit scheduling through the **APP/Website**

- adoption of **digital signature** for contracts

- KB acting as **guarantor for tenants** with good credit score.

Customer Journey for Landlords

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	KB option	APP / Website	Landlord Option
Landlord	**Partnership**	**Listed Properties**	**Fast Track**

Owns a property and can accept tenant offers.

Along with private landlords, KB can partner up with **professional estate developers** to offer both B2B and B2C listings on their platform

Landlords / developers list their properties on KB's **App** and **website**, where prospect tenants can browse through

If Landlords / Developers opt for "**Fast Track**", they give a **pre-approval** to agree to the first tenant's offer that reach the minimum price

Customer Journey for Tenants

APP / Website	Visit Option	Proposal Option	KB's check
Tenant	Property Visit	Proposal + Exclusive	Credit check

Looks for properties to rent on KB's APP / Website

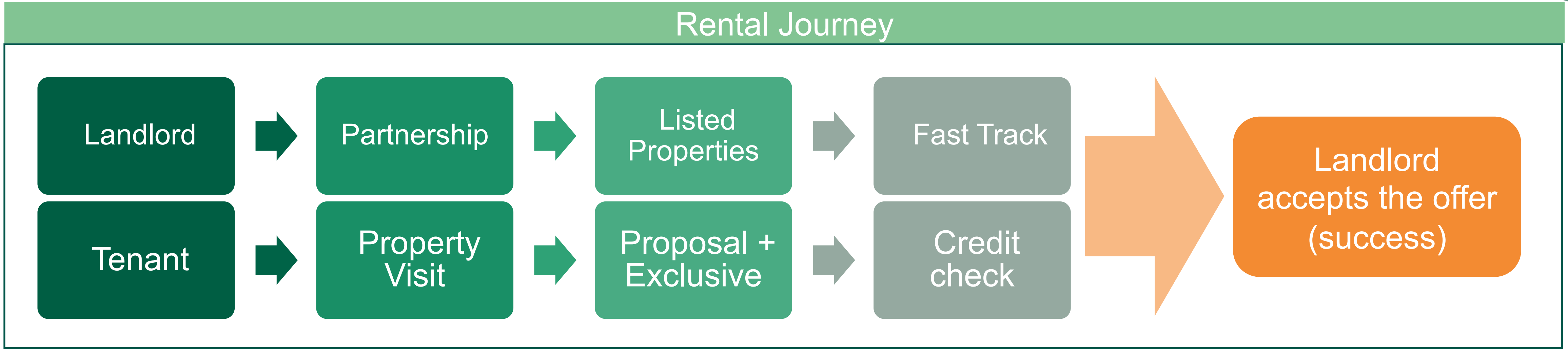
Prospect tenants can **visit properties traditionally** with an agent or **digitally** as a virtual visit (shot by KB's video-maker, more costly for KB)

Proposal to rent the property can be a **default contract** or **customized**

Prospect tenants can opt for an "**Exclusivity**" fee which **freezes other prospects' offers**. (Landlord can still refuse).

Once a proposal has been sent by the prospect tenant, KB does a **credit check** and sends the offer to the landlord only if **credit score is positive** (KB acts as guarantor for tenants).

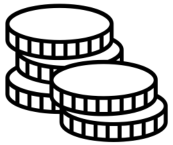
Our objective



When a Landlord accepts an offer, a new rental contract managed by KB successfully comes into place.

We built our model to help KB understand:

1. Which variable has the most significative impact in a closed deal
2. Whether to improve the variable or improve the business model
3. Next steps to drive higher results by closing more deals and cutting costs



Snapshot of Datasets

Data Size

18K+
Data Pieces
10 Variables

- The data comes from original company source;
- It is anonymized and edited to ensure confidentiality

Sample of the data

The screenshot below depicts the first 10 rows of the data:

ID_Proposal	Exclusive	Partner	Custom	FastTrack	Visit	Date_CreditApproved	Date_ContractSent	Date_DealClosed	DealClosed
241246	1	0	0	1	0	2019-12-13	2019-12-13	2019-12-16	1
236129	1	0	0	1	0	2019-12-04	2019-12-05	2019-12-06	1
247413	1	0	0	1	0	2019-12-27	2019-12-27	2019-12-29	1
242206	1	0	0	1	1	2019-12-14	2019-12-16	2019-12-19	1
232076	1	0	0	1	0	2019-11-27	2019-11-28	2019-11-29	1
232319	1	0	0	1	0	2019-11-28	2019-11-29	2019-12-05	1
245013	0	0	0	1	0	2019-12-19	2019-12-20	2019-12-20	1
259667	1	0	0	1	0	2020-01-20	2020-01-20	2020-01-21	1
241540	0	0	0	1	0	2019-12-17	2019-12-17	NA	0
250144	0	0	0	1	1	2019-12-30	2019-12-30	NA	0

1 Exclusive

Categorical Variable:
"1" means that all other possible offers will be frozen and made not available

2 Partner

Indicates whether the property is from a partner **"1"** or if it is a standard one **"0"**

3 Custom

Indicates whether the tenant asked to customize some aspects of the property (**"1"**) or not (**"0"**)

4 Fast Track

The landlord can request to automatically accept the offers (**"1"**) instead of checking it before (**"0"**)

5 Visit

Indicates how the visit will be conducted: in the traditional way (**"0"**) or digitally (**"1"**)

What did we do (model, features, WIP based on modeling)

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1 Feature Engineering

- We introduced 11 additional variables across 4 different dimensions:
  - Start of the month
  - End of the month
  - Day of the week
  - Time from credit approval to contract sent
- We decided to perform classification models over **5 main initial variables** plus **Time from credit approval to contract sent** that were the most relevant ones in our results

2 Practice and Assess Classification Models

- We divided the dataset into three samples, one for training, one for testing and one for validation;
- We practiced classification models below over estimation sample and assess the accuracy in the validation sample
  - Logistic Regression
  - CART
  - xgboost
  - Random Forest
  - Rpart
  - Lasso & Ridge

3 Generate Business Insights

- We synthesized results from previous two stages, trying to :
  - Identify core variables having significant impacts on KB's existing business models;
  - Explore areas to be improved for either lowering cost or generating more revenues for KB;
  - Propose more initiatives to speed up the journey of landing more closed deals.

Conclusions from our chosen model

Through our different models' we got similar results, the logistic regression was picked to exemplify our analysis due the highest AUC...

Confusion Matrix and Statistics

	Reference	
Prediction	0	1
0	448	720
1	238	1382

Coefficients:

	Estimate	Std. Error	z value	Pr(>|z|)	
(Intercept)	0.819444	0.038436	21.320	<2e-16	***
Exclusive1	-0.488126	0.047906	-10.189	<2e-16	***
Custom1	-0.131157	0.068075	-1.927	0.054	.
FastTrack1	1.175079	0.043781	26.840	<2e-16	***
Visit1	-0.507171	0.054821	-9.251	<2e-16	***
TimeApproved_to_ContractSent	-0.127164	0.008049	-15.799	<2e-16	***

- We adopted a **threshold of 75%** (DealClosed mean) which **results in 71% of AUC** and 65% of accuracy
- From the Confusion Matrix we can observe both **specificity and sensitivity to be around 65%**

- Thanks to the logistic regression model, we understood that the **most important variable is the adoption of Fast Track by the landlord, followed by a negative correlation on Digital Visit and Exclusivity Option respectively**
- **Time and Customized contract** also have a **negative impact**, as expected, but less intense than the previous features

Comparison of Models

Models	Improved AUC
Logistic Regression	0.7058
CART	0.7047
Rpart	0.6514
Random Forest	0.6234
xgboost	0.7048
Lasso	0.7054
Ridge	0.7056

Conclusion

- Logistic Regression model is likely to be the most feasible model considering its relatively higher AUC value.

What this means for the business

Thanks to our previous analysis we identified the following action points to increase KB's revenue & profit:

Fast Track

Properties of landlords who opt for Fast Track are more likely to have a fast closed deal.

Actively convince landlords to add the Fast Track option.

Exclusivity Option

The Exclusivity option slows down the renting journey and negatively impacts the number of closed deals.

Evaluate if tenants are paying enough for this option, improve or abandon.

Offline Visits

Traditional offline visits to properties with an agent are less costly and more likely to end up in a closed deal.

Evaluate improving or abandoning the digital visit option.

Profit and potential

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By combining the 3 recommended actions in a wide roll-out scenario KB can...

...increase by 4 p.p. the monthly number of deals closed without increasing the client's database...

… representing an additional ~$0.7MM , already discounting costs and exclusive fee revenue reduction

1. Abandoning the **Exclusivity option** will **cost to KB $0.3MM** in fees not captured

2. For **Visits** two impacts were identified but not added to the initial profit model:
   - The **"Digital Visit" project** that is currently a big investment of the company should be paralyzed and better analyzed since there is a negative correlation
   - The current cost of a traditional visit with an agent is inherent to the current business model, **fomenting the normal visits** can be a possible lever too

3. **Fast track** should be pushed as much as possible - the **target is to reach 83%** (actual 66%)
   - To achieve that KB need to **move half of the properties from non – Fast Track to Fast Track** by:
     - Changing the feature from **opt-in to opt-out in the app and web-site**
     - Following up by **phone call to the landlord** who opted out and try to persuade him

Next steps

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Objectives for Next Steps

- Our next step is to test the feasibility of recommendations proposed before by exploring:
  - Any other **key variables highly relevant to deals closure**;
  - Any significant **seasonal trends by expanding the dataset at a longer time series**;
  - Any non-statistical interventions/attempts which lead to **uptick in deals closure**;
  - If there are **cause-and-effect relations across variables we've synthesized so far**

Potential Approaches to Take

- We are to deploy a three-stage approach under a controlled environment and compare results and potential effects of our recommendations before rolling them out to the mass.

IGNITE

Identify potential risks/pain points once recommendations executed

INCUBATE

Prototype solutions by training data in a controlled settings and optimize models performed before

INDUSTRIALIZE

Iterate the model until it is feasible to apply to larger dataset and accurate in validating our recommendations.

Thank you!

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