DRIVING GROWTH

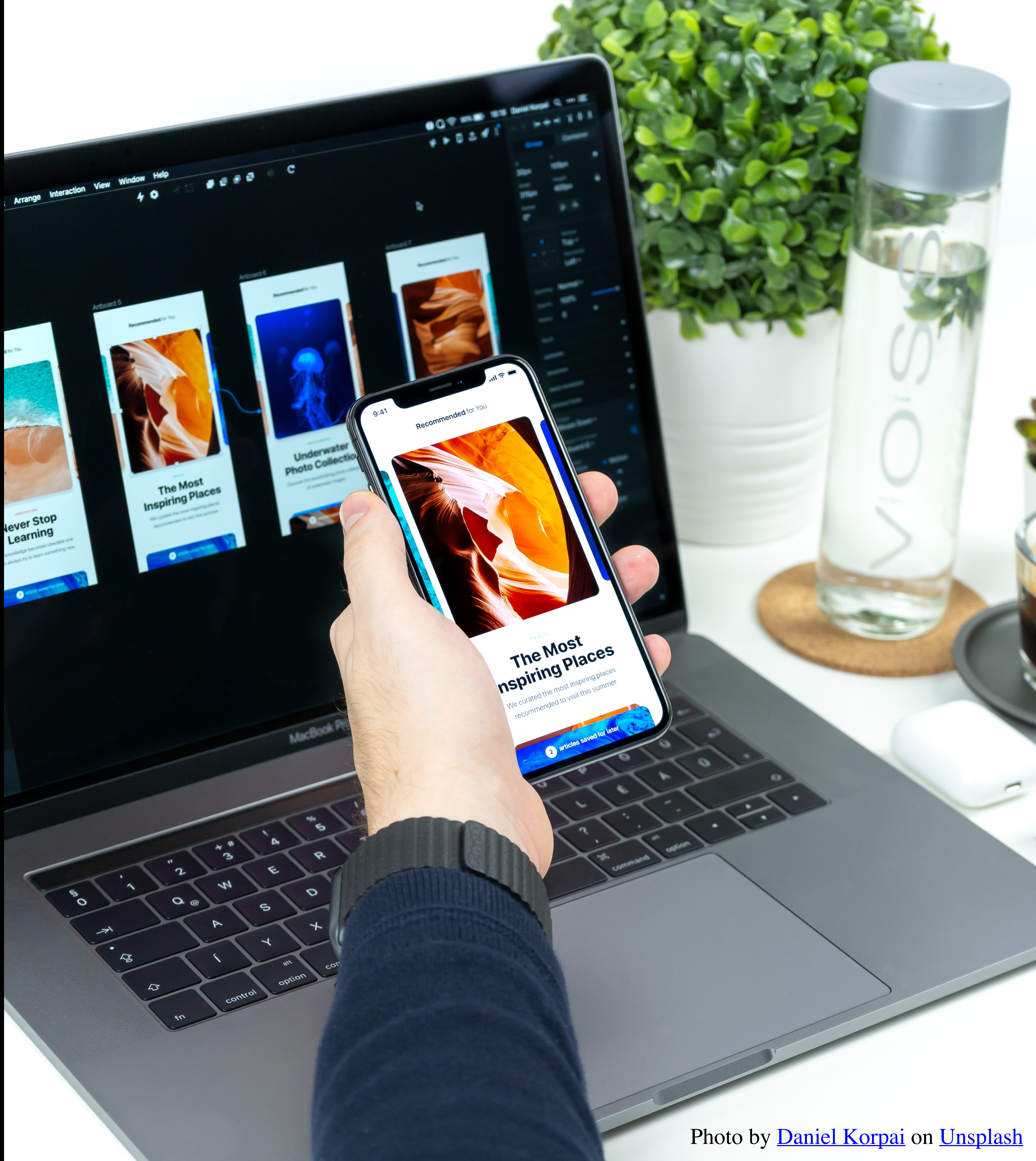
COMPANY A CASE

Optimizing Long Term Profit

- Contents
  - Optimizing CAC with targeted ads and customer segmentation
  - Optimizing LTV with personalized offer powered by recommender system
  - Deployment demo
  - Methodology

OPTIMIZING CAC

TARGETED ADS



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Google facebook YAHOO! Microsoft

MediaMath datalogix turn RUBICON PubMatic Make every impression count

OpenX pulsepoint m6d appnexus Jumptap Admeld

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EXPERIMENT DESIGN

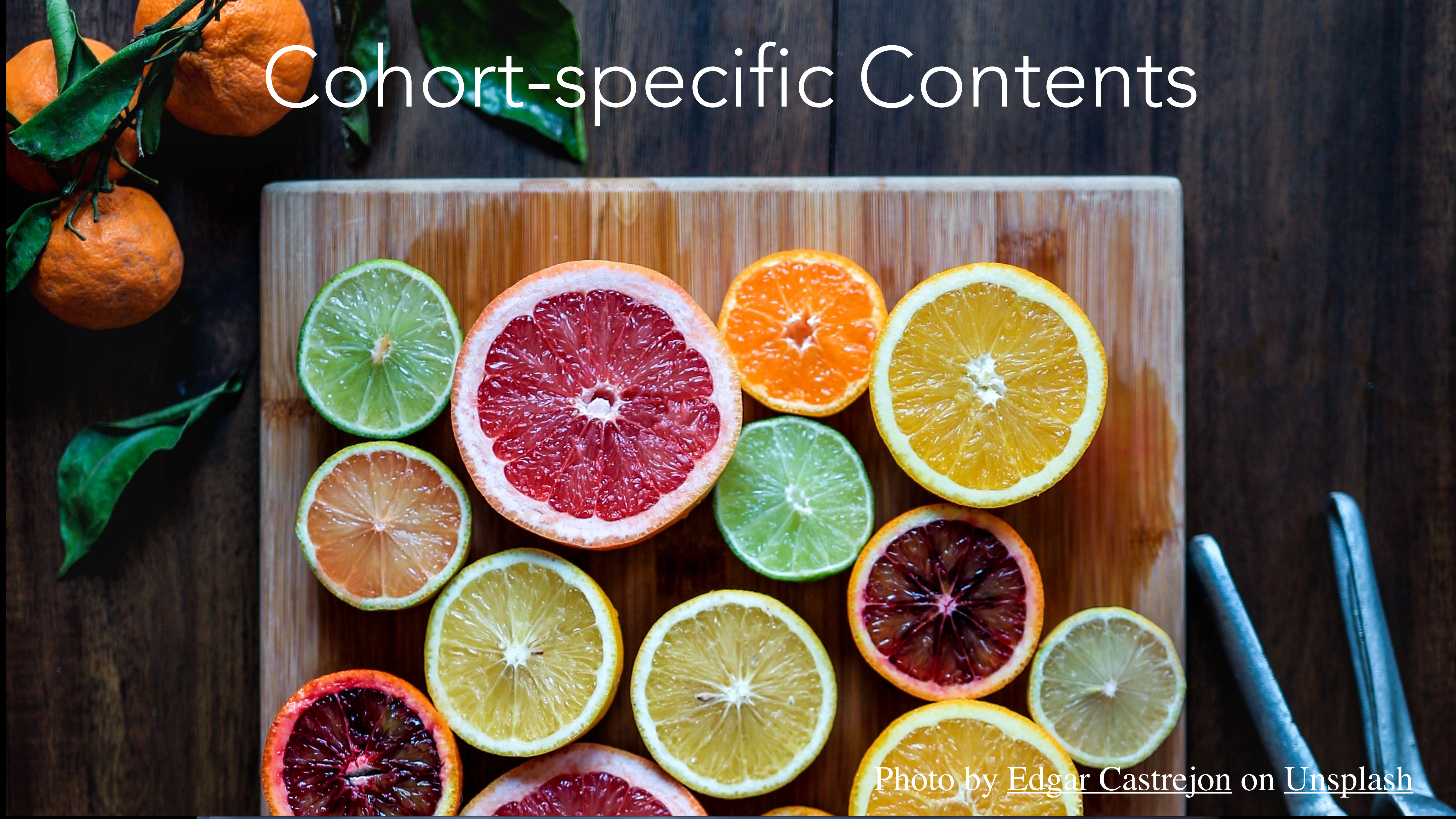
A/B testing of cohort-specific contents vs. top selling product content

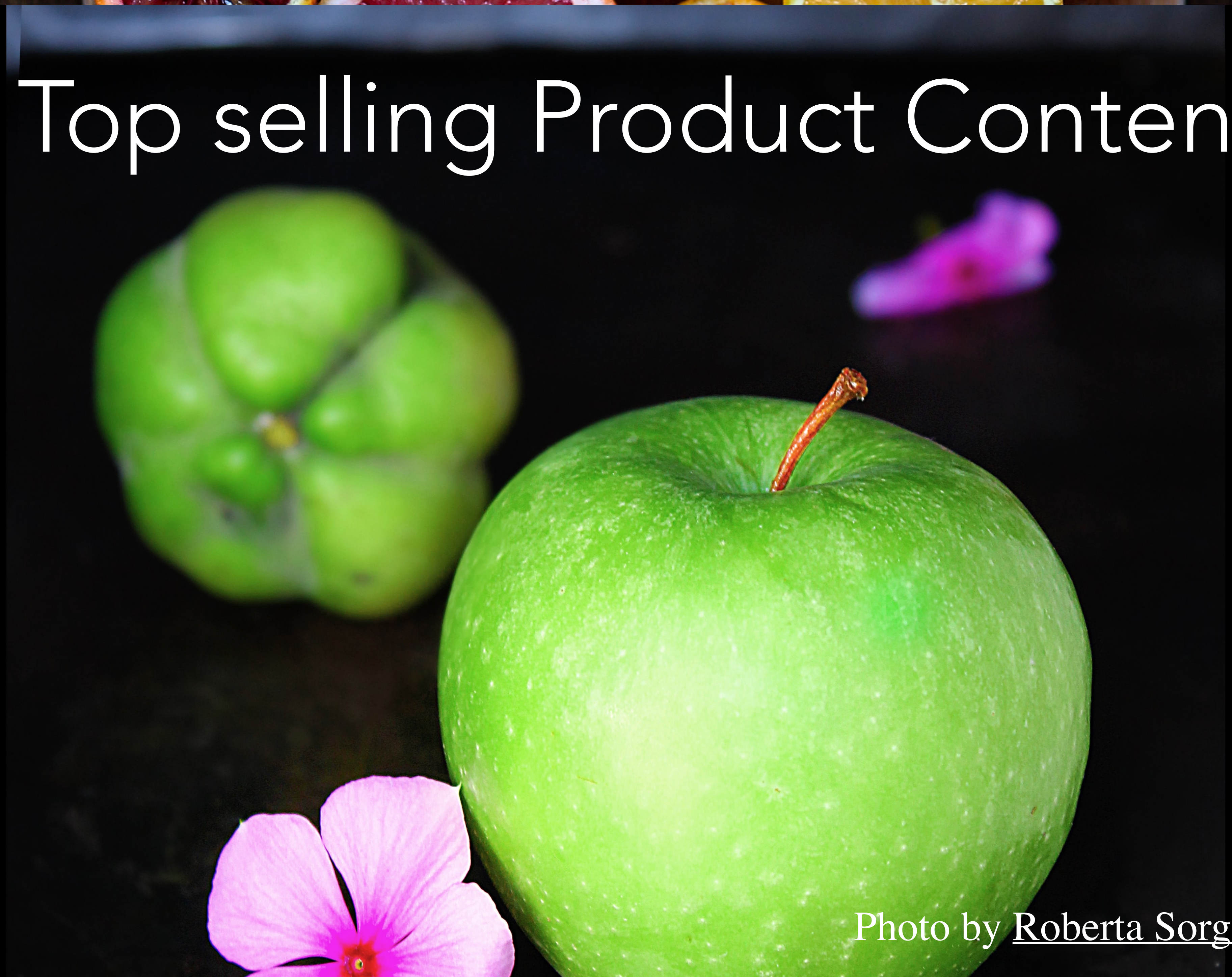
MEASUREMENTS

Ad-click landing page per dollar spent
Page scroll 70% per dollar spent
Product document download per dollar spent

Level of engagement can be converted into implied new customer gained by looking at historical data e.g. 2% of Page scroller ended up buying a policy.

CAC = #new customers / $ ads spent





CONTENTS BY CUSTOMER COHORT

('c.25-29', 'm', 'region_3'):

{'prod_rec': 'savings',

'median_insured_amt': 500,000},

('c.25-29', 'm', 'region_8'):

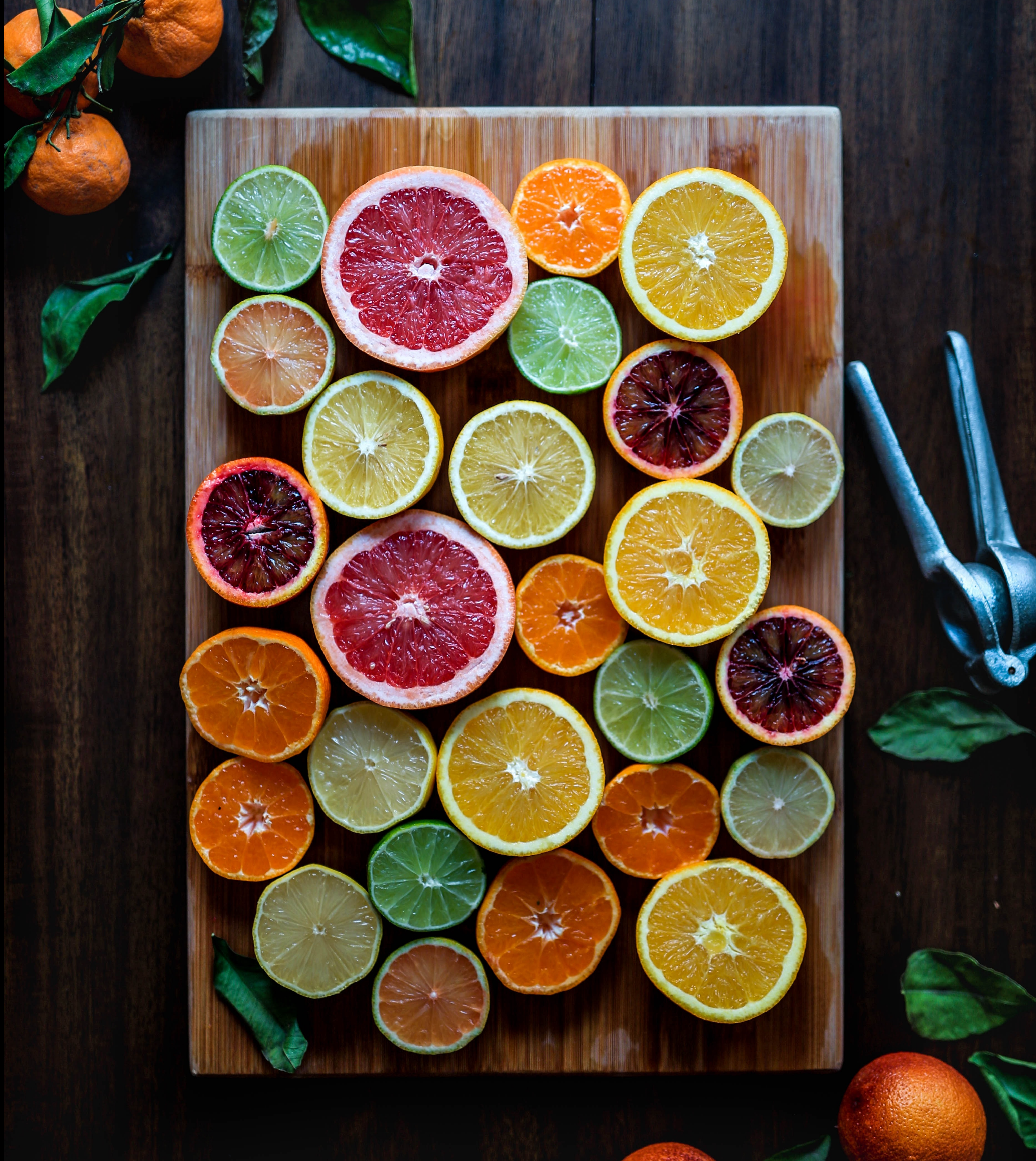
{'prod_rec': 'health',

'median_insured_amt': 25,000},

('d.30-34', 'f', ‘region_1'):

{'prod_rec': 'retirement',

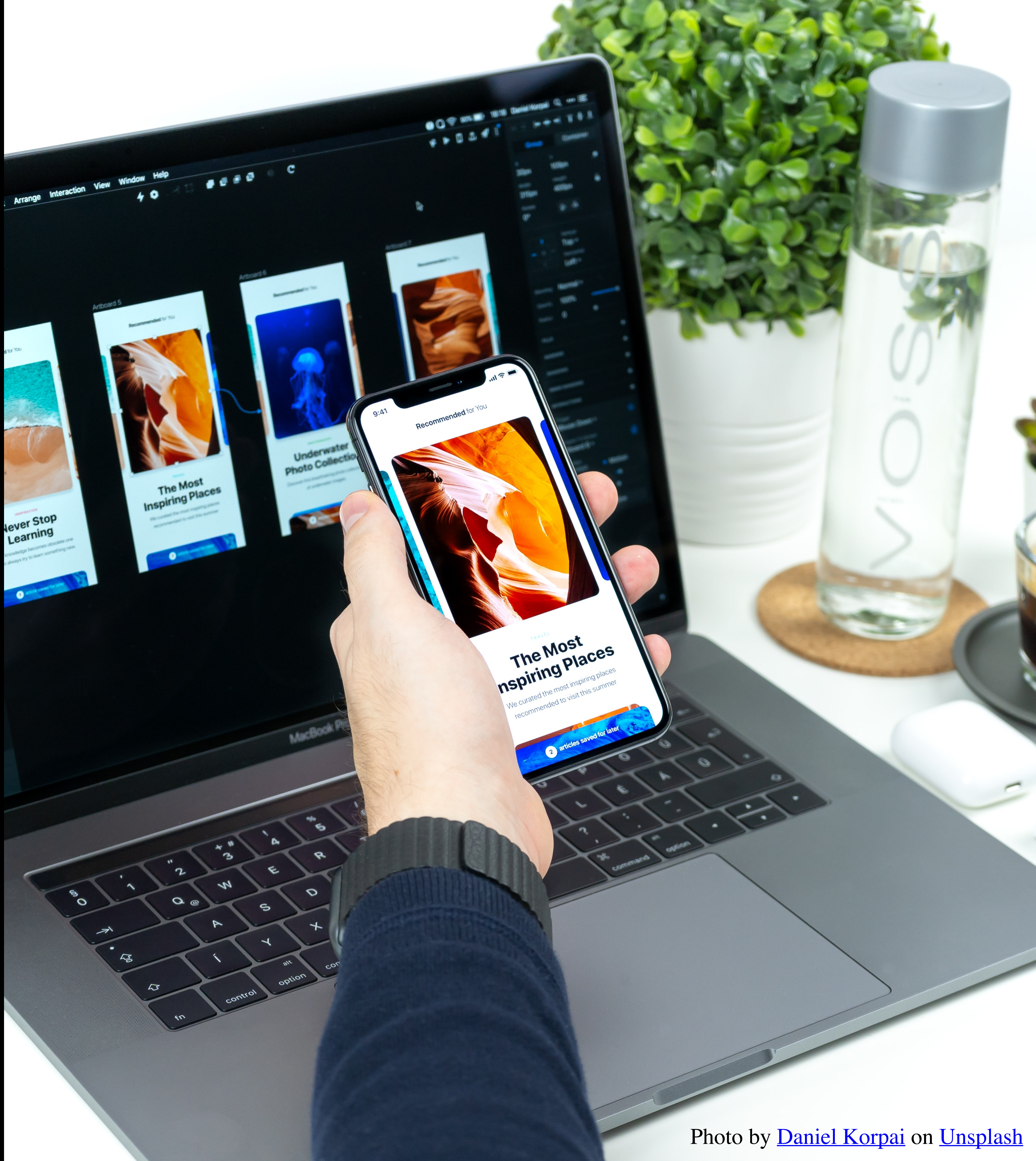
'median_insured_amt': 150,000}



OPTIMIZING LTV

PERSONALIZED XSELL OFFER

POWERED BY RECOMMENDER SYSTEM



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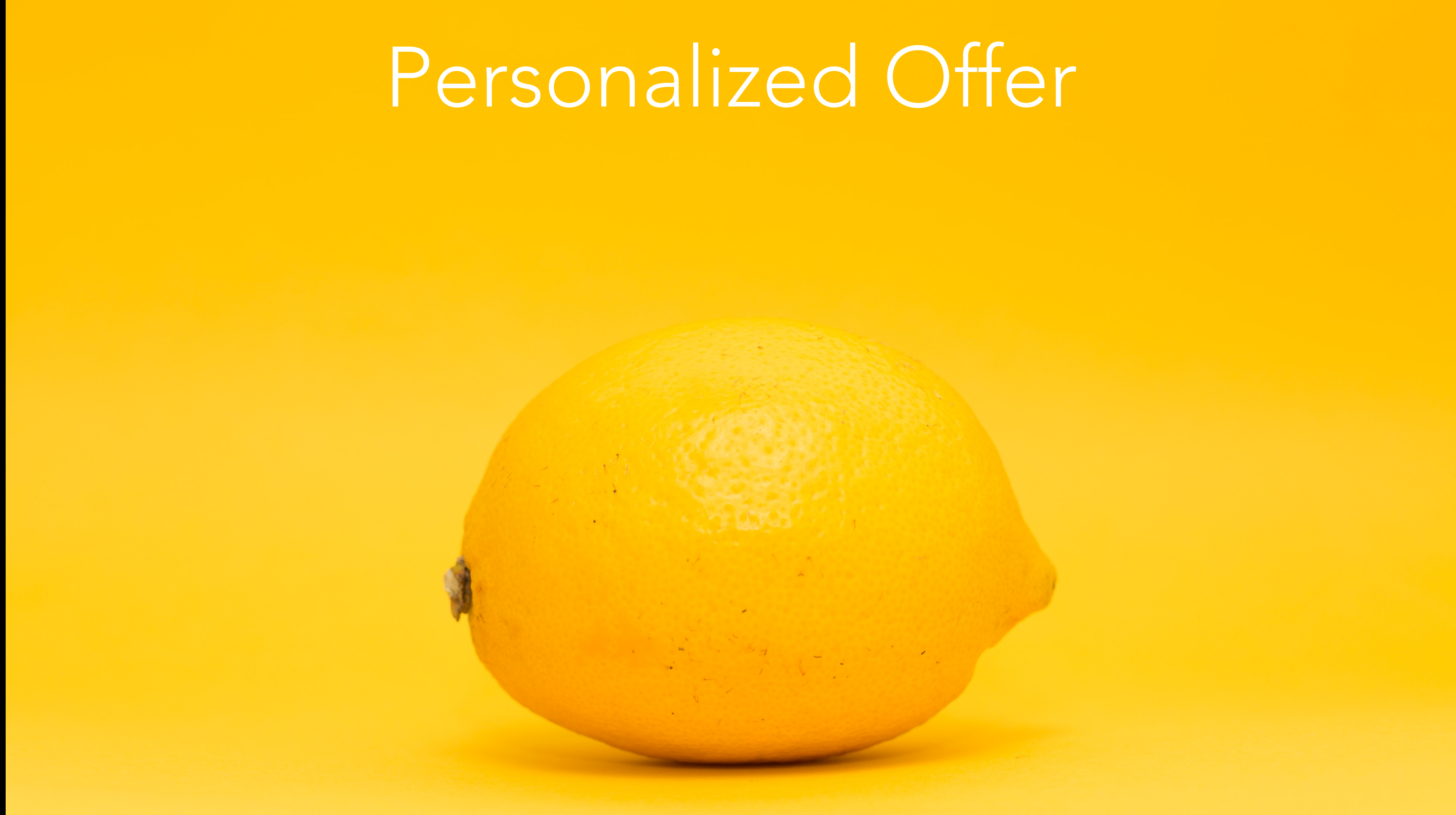
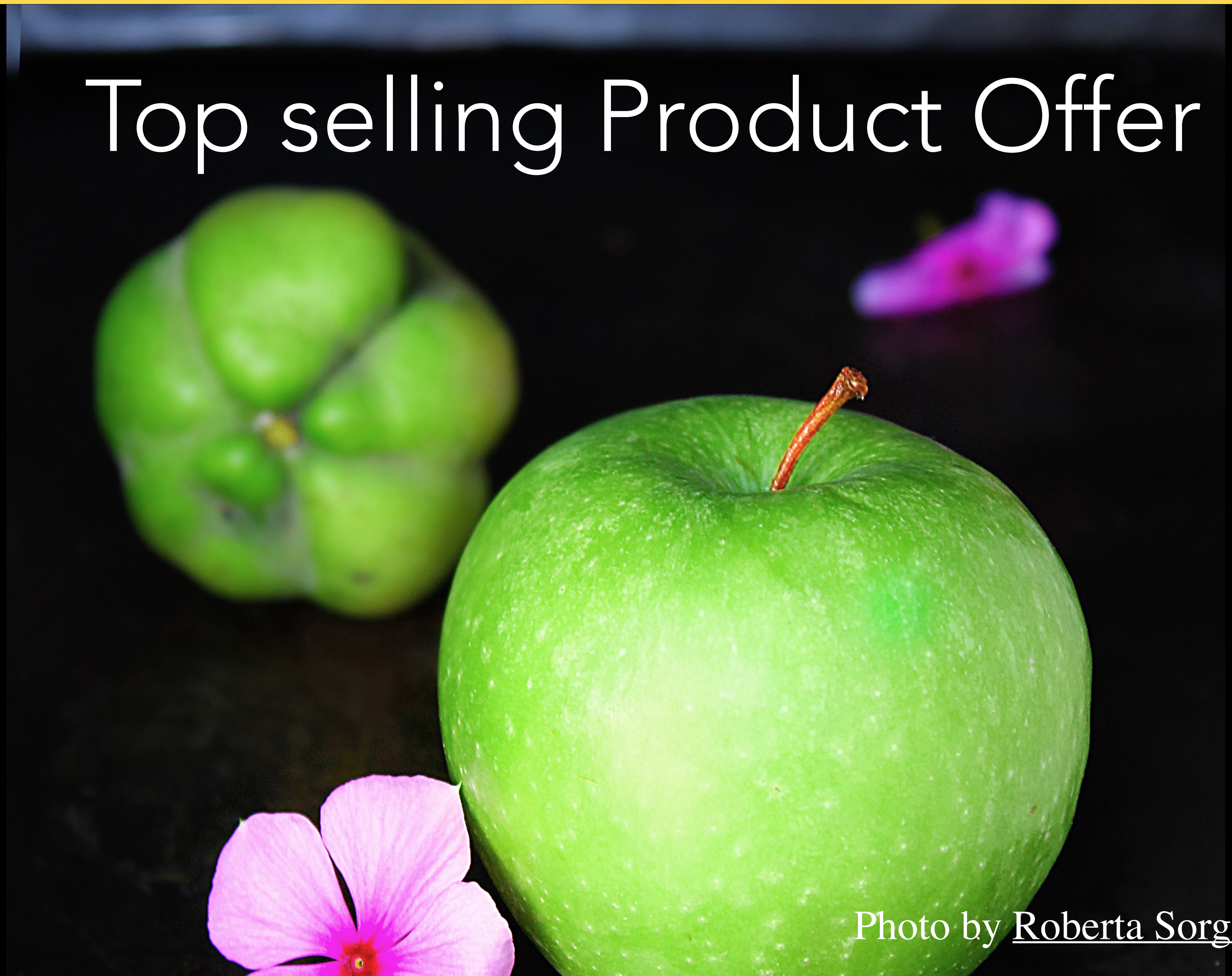
EXPERIMENT DESIGN

A/B testing of offering product recommended by the model vs. top selling product content

MEASUREMENTS

- uplift in conversion rate (#policy sold/ #offer)
- quarterly measure of LTV per customer
  (present value of expected premium paid throughout customer's expected tenure less present value of expected claims)





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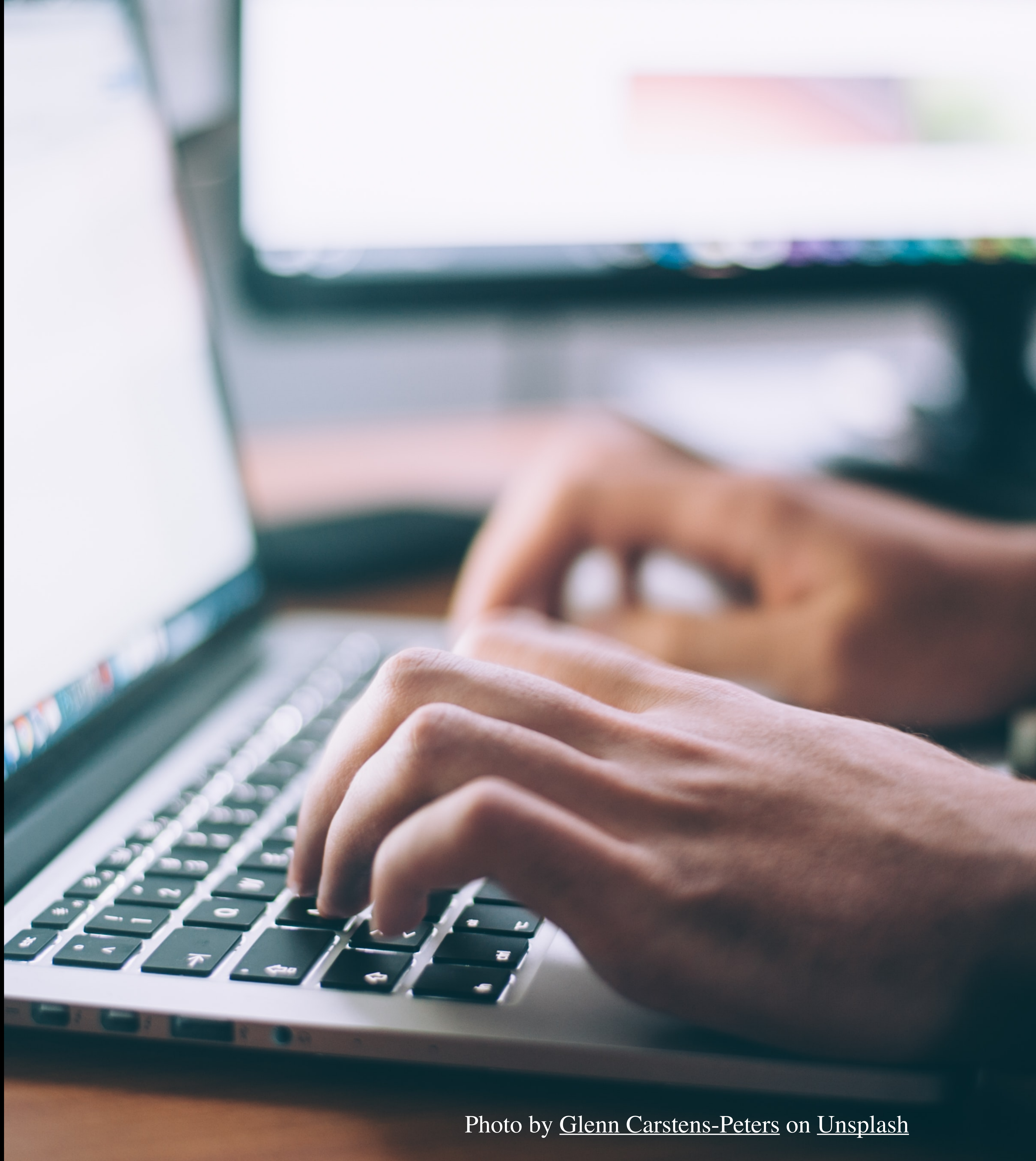
DEPLOYMENT DEMO

METHODOLOGY



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METHODOLOGY

- Multiclass Classification [‘retirement', 'protection', 'investment', 'health', ‘savings']
    - GradientBoostingClassifier, RandomForestClassifier
- Features
    - ['health_insured_amt_acc', 'investment_insured_amt_acc', 'protection_insured_amt_acc', 'retirement_insured_amt_acc', 'savings_insured_amt_acc', 'ul_insured_amt_acc', 'self_insured_amt_acc', ‘dependent_insured_amt_acc']
    - [‘health_anp_acc', 'investment_anp_acc', 'protection_anp_acc', 'retirement_anp_acc', 'savings_anp_acc', 'ul_anp_acc', 'self_anp_acc', ‘dependent_anp_acc’]
    - [‘lapsed_acc', 'surrendered_acc', 'inforce_acc', 'others_acc', 'cancelled_acc', ‘claimed_acc'],
    - [‘policy_count', 'cust_tenure_months', 'cust_recency_months', 'first_product_cat', 'latest_product_cat', 'owner_age_grp', 'owner_gender', 'owner_occupation_grp', 'region_dummy']

MODEL METRICS

Pipeline

1) Preprocessor: transform features, features selection

2) Classifier: GradientBoostingClassifier, RandomForestClassifier

```python
pipe = Pipeline(steps=[('full_preprocessor', feat_select_pipe),
                       ('clf',GradientBoostingClassifier())]) #dummy

k_fold = StratifiedKFold(n_splits=5, shuffle=True, random_state=0)

# Hyperparameters

param_grid = [{'clf':[GradientBoostingClassifier()],
            'clf__n_estimators': [100],
            'clf__max_depth': [3,4,5],
            'clf__min_samples_leaf': [2,3],
            'clf__learning_rate': [0.1,0.05,0.03,0.01]
            },
            {'clf':[RandomForestClassifier()],
            'clf__n_estimators': [500],
            'clf__max_depth': [4,5,6],
            'clf__max_features':['sqrt'],
            'clf__min_samples_leaf': [2,3]}]

best_model = GridSearchCV(pipe, param_grid = param_grid, scoring='accuracy',
                          cv = k_fold, n_jobs = -1, verbose = 1)
```

Pipeline

Metrics

```
classifier: GradientBoostingClassifier(learning_rate=0.01, max_depth=4, min_samples_leaf=2)
Model Accuracy: 0.751
Precision of postive cases: 0.75
Recall of postive cases: 0.75
F1 Score of postive cases: 0.74
```